DOCTOR OF PHILOSOPHY

Remote sensing of land cover changes in the Jeffara Plain, North-West Libya

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University of Dundee

UNIVERSITY OF DUNDEE

REMOTE SENSING OF LAND COVER CHANGES IN THE JEFFARA PLAIN, NORTH-WEST LIBYA

By

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Abstract

In Libya groundwater is the key source of freshwater, providing an essential supplement to surface water sources. Libya is mostly arid and semiarid and sparsely populated large North African country with annual average precipitation rates of 200 mm. More than 95% of the country receives less than 100 mm, and as consequence, recharge of groundwater is extremely limited. Groundwater availability and quality are also vulnerable both to climate change and over-abstraction, and in regions where the water table has lowered there has been a consequent impact on agricultural activities.

This research examines the impact of water table change on land cover (particularly agricultural activities) in part of the Jeffara Plain NW Libya, during the period 1988 to 2000 using remotely sensed data. Landsat Thematic Mapper 5 images from 1988, 1992, 1996 and 2000 have been used in addition to various thematic maps of the study area and bore-hole data to assess the nature and extent of change. A supervised Maximum Likelihood approach (ML) was used to classify each image into land cover classes that were likely to have been directly affected by groundwater changes, with resulting accuracies between 67% and 76%, obtained. The change in the extent of land cover classes in all images was clearly visible and occurred as either an increase or a decrease between successive dates. From the questionnaire survey, and interviewing local farmers, it is clear that groundwater changes (quantity and quality) have had a significant impact upon the vegetation cover and agricultural activities of the area.To verify the changes and assess new tools for image classification, a second approach was tested with the application of Artificial Neural Networks (ANN) as alternative image classification method, and gave results with high accuracy (over 90%), greater than those from the ML.

Results from both methods illustrate a similar and comparable pattern of change in the vegetation cover, agreeing with the evidence from a questionnaire results and field data. Change in agricultural activities was readily apparent, especially the reduction in areas of citrus fruit and other types of fruits, which require abundant supplies of irrigation water, (64.6% reduction from 2000 compared to 1988). The questionnaire survey method was effective and helpful to link these changes to groundwater changes.

To add to a limited set of borehole data, questionnaires survey responses helped to articulate the links between groundwater and changes in agricultural land cover, helping to interpret the changes seen in a socio-economic context.

ACKNOWLEDGMENTS

This thesis is the reward of four years of research at Dundee University. Although I have enjoyed these years very much, completion would not have been possible without the support of so many people.

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Special thanks to my wife and sons who have given me support over the course of my PhD study, they have all helped to make my time away from home comfortable and memorable. My final thanks are to my parents; without their unwavering support and consideration I would not have got this far.

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List of Abbreviations

ACSAD	Arab Centre for the Studies of Arid Zones and Dry Lands
ANNs	Artificial Neural Networks
AOI	Areas of interest
ASCII	American Standard Code for Information Interchange
AVHRR	Advanced Very High Resolution Radiometer
BGIS	Ball Global Imaging System 2000
BRSC	Biruni Remote Sensing Centre
DN	Digital Number
DOS	Dark Object Subtraction
DPIWE	Department of Primary Industries, Water and Environment
EMWIS	Euro-Mediterranean water Information System
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper plus
FAO	Food and Agricultural Organization
GCPs	Ground Control Points
GEA	General Environmental Authority
GIS	Geographic Information System
GMMR	Great Man- Made River
GLCM	Grey Level Co-occurrence Matrix
GPS	Global Positioning System
GWL	Groundwater Water Level
HRV	High Resolution Visible
IFOV	Instrument Field Of View

LAI	Leaf Area Index
LGWA	Libyan General Water Authority
MEIRS	Medium Resolution Imaging Spectrometer
ML	Maximum likelihood
MLP	Multi Layer Perceptrons
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NLAPS	National Landsat Archive Production System
NOAA	National Oceanic and Atmospheric Administration
PCA	Principal Components Analysis
R	Red
RMS	Root Mean Square
SMA	Spectral Mixture Analysis
SNR	Signal-Noise Ratio
SPCA	Selective Principal Components Analysis
SPOT	(Satellite Pour l'Observation de la Terre) (Satellite for the Observation of the Earth)
TM	Thematic Mapper
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VIs	Vegetation Indices
WGS84	World Geodetic System 1984

WJS	Western Jamahiriya System
WRS	Worker Registration Scheme

CHAPTER ONE
Introduction

1.1. Background

Water is a commodity that will have a profound effect on the World within the next few decades, drastically changing the way in which it is viewed as a resource (Grossman, 2004). Groundwater is a key source of drinking water that is essential to life on Earth. The Earth has an estimated $330\times10^6\ m^3$ of water, with most of it occurring as non-potable seawater. Groundwater makes up only a small proportion, approximately 0.06%, of the Earth's available water. However, this relatively small volume is critically important because it represents 98% of the freshwater readily available to humans (Schwartz and Zhang, 2002). Worldwide, 50% percent of municipal water supplies come from groundwater (Llamas, 2004; Michael, 1998) and in some regions the proportion is much higher. Generally though, groundwater is particularly important as a source of drinking water for rural and dispersed populations. Seventy percent of all groundwater withdrawals worldwide are used for irrigation, particularly in arid or semi-arid regions (Llamas, 2004).

The exploitation of these key finite resources presents a significant environmental challenge. The natural recharge of aquifers in semi-arid and arid climates does not have a linear relationship with precipitation. In dry years recharge might be negligible or even negative due to evapotranspiration or evaporation from the water table. Significant recharge may occur only once per decade (Llamas, 2004).

Libya is a country that suffers from limited surface water resources because most regions are either semi-arid or arid. For example, the Jeffara reservoir in western Libya is witnessing excessive draw down as it is located in the most populated and intensive agricultural region of Libya (Nasr, 1999). As it has little or no renewable water resources, Libya relies heavily on groundwater for satisfying its ever-increasing water needs with minor contributions from springs, wadis, surface runoff and dams. The consequent over-reliance on groundwater for meeting the demands for water has resulted in the excessive depletion of the fresh groundwater stock. The situation is being exacerbated by the lack of adequate recharge to replenish the water withdrawn from the various aquifers. The highest rainfall occurs in the northern Tripoli region (Jabal Nafusah and Jeffara Plain) and in the northern Benghazi region (Jabal al Akhdar), these two areas being the only ones where the average annual rainfall exceeds the minimum value (250–300 mm) considered necessary to sustain rain-fed agriculture (Pallas, 1980). However, even in these areas groundwater is required to irrigate crops and sustain important agricultural production.

Changes in groundwater availability and/or quality are manifest in changing vegetation patterns (Sophocleous, 2001), and are also a key driver for desertification (Ben Mahmoud *et al.*, 2000; Oune, 2006). For example, a fall in groundwater level has had negative effects on a vegetation cover in the Wadi al-Ajal which is located in the Fezzan region of south-western Libya (Brooks *et al.*, 2001), causing plant stress and eventual removal, which in turn can exacerbate soil erosion and landscape degradation (desertification).

Previous studies have tended to concentrate upon the effects that surface activities (land use) have had upon groundwater supplies (e.g. Al-Senafy and Abraham, 2004; Candela *et al.*, 2008; Ma *et al.*, 2005; Mahvi *et al.*, 2005). For example, Droubi (1996) noted that agricultural activities are the main sources of negative effects on groundwater in Arabic countries due to the overexploitation of aquifers (e.g. water quality with increasing salinity) and there is a clear correlation between the intensity of agricultural activities and groundwater pollution (Droubi, 1996). This clear inter-relationship between groundwater and land use activities indicates that the availability of groundwater will also have an impact upon the type of land use activities present within a region. In times of groundwater change (in both quantity and quality), it would be reasonable to suppose that land use activities will change in accordance with their demand for irrigation water. To date, few studies have documented changes in land use associated with changing groundwater status. This project aims to describe and explain the land use changes associated with groundwater availability in an area of northwest Libya.

1.2. Groundwater (Aquifers)

Generally, groundwater does not occur as large underground lakes or streams, rather it fills irregular spaces within rock fractures or between particles of sand, gravel or clay. Whereas water in a stream may move at several meters per second, groundwater may move only a few meters per month or even per year (Grossman, 2004). The major exception to this general rule is in limestone areas where groundwater may flow rapidly through large underground channels and caverns. The geological units within which groundwater moves through are called aquifers.

Aquifers have the capability of both storing and transmitting groundwater (Schwartz and Zhang, 2002). They are defined as permeable rocks that store groundwater and allow it to flow readily into a well or borehole and its extraction for human use is a form of mining (Grossman, 2004; Michael, 1998). These can be layers of permeable sand, gravel, or other soil materials, or a section of bedrock with interconnected fractures through which water can flow. The groundwater layer in which all available spaces are filled with water is called the saturated zone. The dividing surface between the saturated zone and overlying unsaturated rock or sediments is called the water table. Aquifers which are located near coastlines can experience saltwater intrusion (Grossman, 2004; Maslia and Prowell 1990), where saltwater mixes with fresh water from the aquifer, rendering the water unusable (El Fleet and Baird, 2001). Heavy abstraction of groundwater can deplete aquifers until there is little or no fresh water available to those who depend upon it.

Non-renewable aquifers are often described in the literature as "fossil" aquifers. These are aquifers with no appreciable modern recharge and which cannot discharge naturally. Most often found in arid climates, fossil and other non-renewable aquifers are an important water resource for many nations. Some of these aquifers are transboundary, such as the Nubian Sandstone aquifer underlying Chad, Egypt, Libya and Sudan. Located at depths ranging from a few meters to a few hundred meters, the water in this aquifer is estimated to be as much as 35,000 years old (EMWIS, 2005). While the overlaying strata are still relatively permeable, present-day recharge rates range from miniscule to nil, contingent on the occasional rain and flash flood (Eckstein, 2005).

Aquifers can be further sub-divided into unconfined (open) and confined (closed) systems.

1.2.1. Unconfined aquifers (Open aquifers)

Unconfined aquifers (also called water table aquifers), are bounded by a free surface at the upper boundary, meaning that they have one layer of impermeable material beneath the saturated zone (Figure 1.1). The water infiltrates through permeable materials that make up the unsaturated zone (where pore spaces are only partially filled with water) into the saturated zone of the aquifer (where all the pore spaces are filled with water). Where groundwater is in direct contact with the atmosphere through the open pore spaces of the overlying soil or rock, the aquifer is said to be unconfined. The upper groundwater surface in an unconfined aquifer is called the water table which is the upper limit of saturation (Michael, 1998; Schwartz and Zhang, 2002). The depth to the water table varies according to factors such as the topography, geology, season and tidal effects, and the quantities of water being abstracted from the aquifer. Unconfined aquifers are usually recharged by rain or stream water infiltrating directly through the overlying materials. Typical examples of unconfined aquifers include many areas of coastal sands and alluvial deposits in river valleys (DPIWE, 2005).

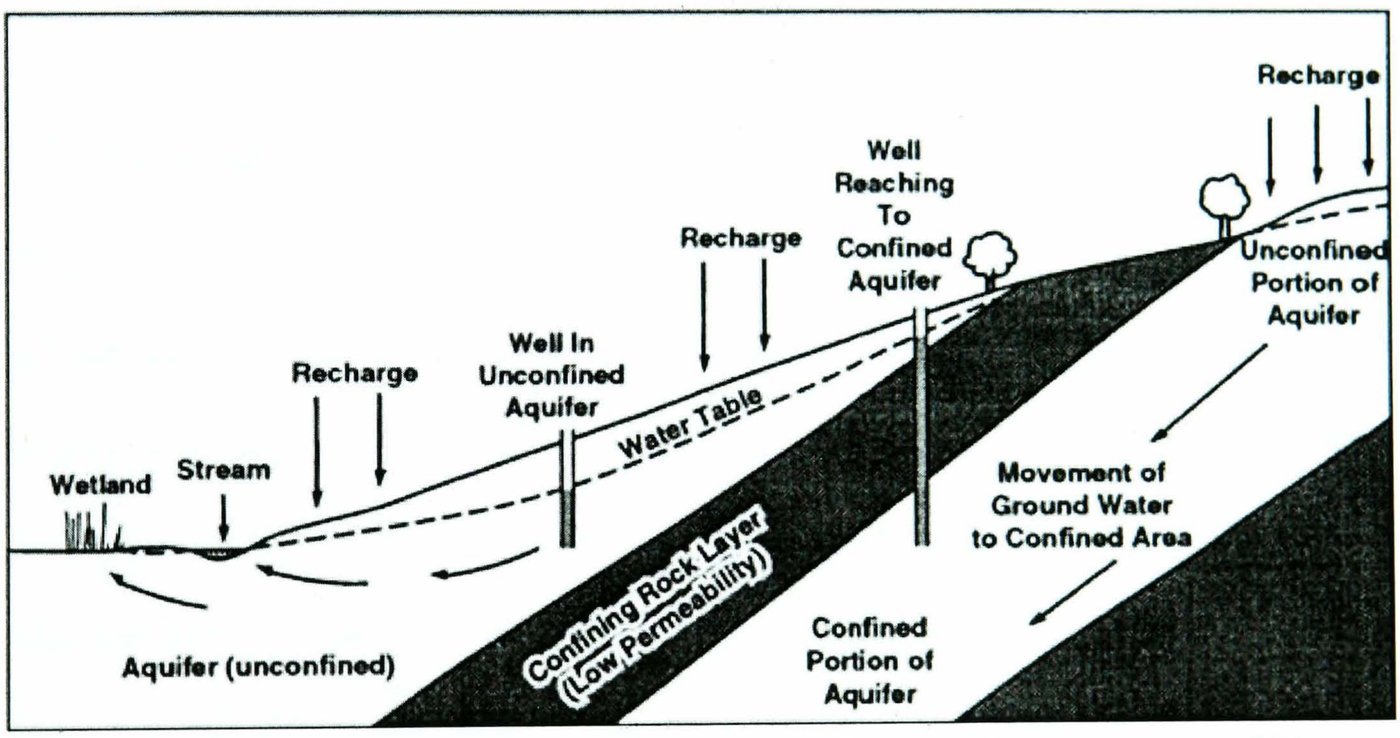

Figure 1.1. Confined and unconfined aquifers (Source: American Ground Water Trust; 2008).

1.2.2. Confined aquifers (closed aquifers)

Confined aquifers, which are also called artesian aquifers or pressure aquifers (Figure 1.1) are bounded from above by another layer of impermeable rock and are not recharged by the hydrologic cycle. They hold their water under pressure and, if a well is tapped into such an aquifer, the water will rise to the height determined by the amount of pressure within it (Schwartz and Zhang, 2002). If this height, known as the piezometric surface, is above the land surface there is the possibility of an artesian well. Such aquifers may be located below unconfined aquifers and have an entirely different shape (Thomas, 1992).

A confined aquifer, compared to an unconfined aquifer, is separated from other aquifers and the land surface by a confining layer. This confining layer is usually a clay or silt-sized sediment, tightly cemented rock, or a mixture of sediment sizes such as found in glacial till. The confining layer inhibits the vertical movement of water into and/or out of the aquifer. The degree to which that water movement is bounded depends on the thickness and composition of the confining layer (Darryll and Deon, 1977).

1.3. Importance of groundwater

There are good economic reasons for widespread dependence on groundwater. In its natural state groundwater is usually of excellent quality and can be used with no costly treatment or purification (Trautmann *et al.*, 1998). It can be inexpensively tapped adjacent to the point of use, thereby saving the costs of transporting water long distances. In addition, costly storage facilities such as water tanks or towers are not needed. Surface water, on the other hand, usually requires storage and treatment, which are relatively expensive and difficult to manage without considerable technical resources. For rural residents relying on individual wells, groundwater is often the only available water supply and for many communities it is by far the least expensive option for public water supply systems (Trautmann *et al.*, 1998).

The water supplies of many cities in the Arabic region (arid and semi-arid) are being drastically reduced. Water that farmers depend on to irrigate their crops is becoming scarce (Droubi, 1996). There are particular sensitivities and technical problems with groundwater systems. Generally, groundwater systems react slowly to surface impacts such as land use change and land management which impact upon groundwater contamination and pollution. Crucially, when damage is done the effects are extremely high in both social and financial terms (Newson, 1997).

The increase in the global population, combined with rising standards of living in some developing countries, will produce enormous strains on land, water, energy, and other natural resources, therefore the growing population and its demand for water is one of the most serious global issues facing mankind at present (Sophocleous, 2001). The availability and quality of freshwater resources around the World are of growing concern to the international community. Human wellbeing, ecosystem health and function, economics and politics all depend on how much, when, and where water is available (Sophocleous, 2004). Groundwater is also important because of various physical processes that it impacts upon, such as moving economic metals (e.g. lead and zinc) across groundwater flow systems (Schwartz and Zhang, 2002).

1.4. Water resources in Libya

The Arab region is one of the most dry and water-scarce zones in the world (Droubi, 1996). An audit of water resources in Libya was carried out by LGWA and General Environmental Authority (GEA) (Figure 1.2). This confirmed that groundwater is the main source of water supply, meeting 88% of the water needs.

According to the water balances of the groundwater basins in Libya, a severe deficit in water supply occurs in the Jeffara Plain basin and a moderate deficit in the Jebal El-Akhdar basin (Figure 1.3). The Jeffara Plain has the highest water demand in Libya, as it is the most populated, and hence the biggest negative water balances (Ben Mahmoud *et al.*, 2000).

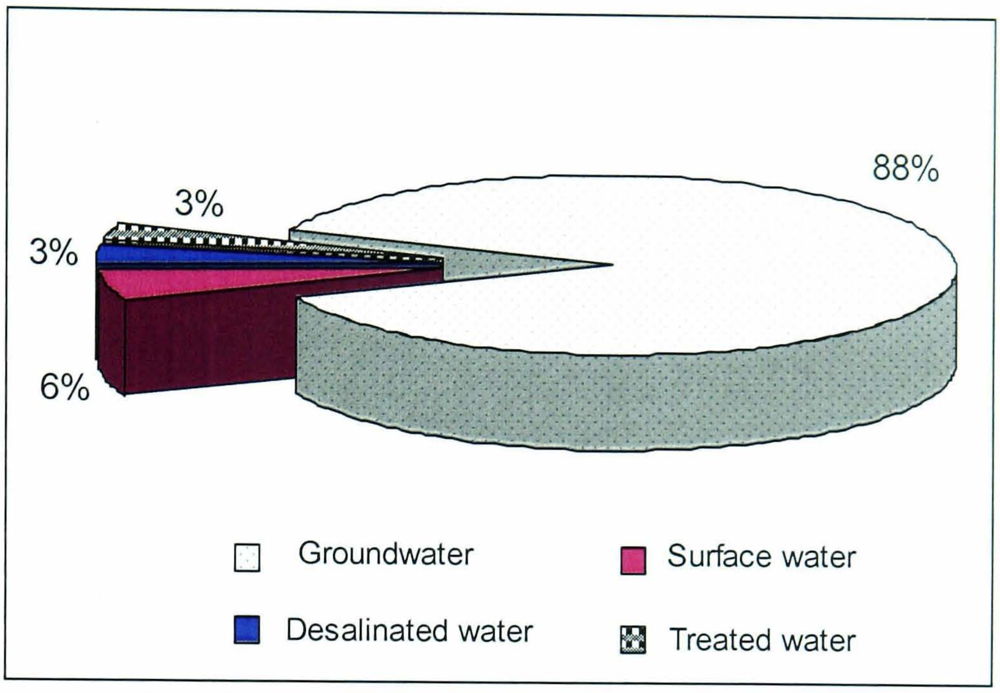

Figure 1.2. Water resources in Libya, 2000, (LGWA, 2002).

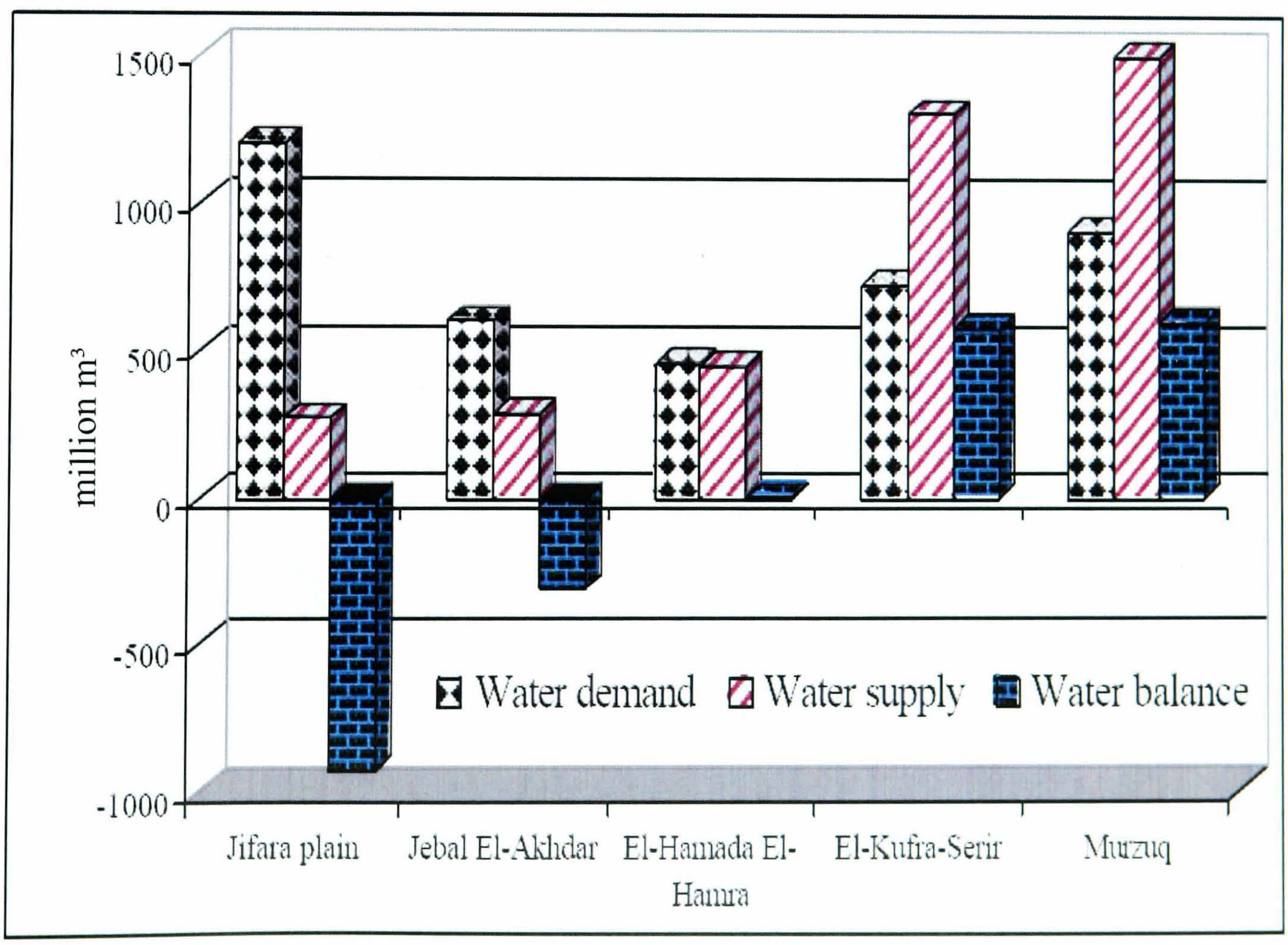

Figure 1.3. Water balance in the groundwater basins in Libya (1995), (Ben Mahmoud et al., 2000).

Crucially, it is noted that in Libya the amount of water withdrawn from groundwater is over eight times its renewable water resources. The gap, largely manifested as water stress in vegetation in northern areas, is filled largely by the pumping of fossil groundwater (FAO, 2001). Furthermore, the water needs of Libya are growing rapidly and it is predicted that the water deficit will be more than 4 billion m^3 $year^{-1}$ in 2025 (FAO, 2001) (Figure 1.4). In the case of the Tripoli region, water is used extensively for both domestic supply and agricultural irrigation, while there is no any regulation control the water extraction. On the other hand still the spring system is the most common irrigation system use in Libya. Most of this demand has been met until recently by the upper aquifer, although some limited abstraction from lower aquifers takes place. The demand has increased dramatically over the past 30 years and is expected to rise steeply with population growth and agricultural development (El Fleet and Baird, 2001), and will rely on exploitation of the southern basins.

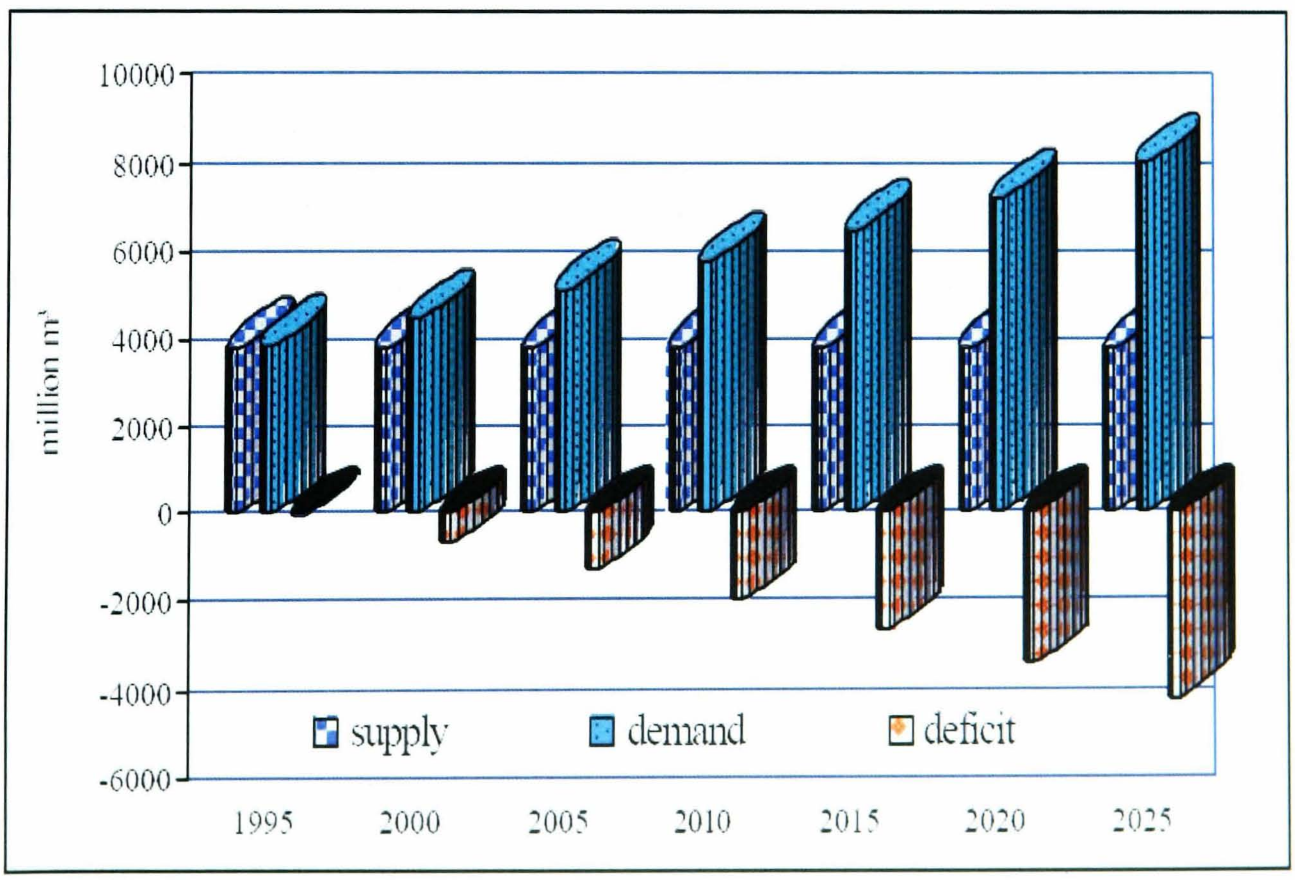

Figure 1.4. Water deficit in Libya, 1995-2025. The water demand is increasing gradually with the shortage of groundwater as the main source (El-Tantawi, 1998).

As water demand has increased in the northern part of Libya, this has led to the development of the Great Man-Made River (GMMR) project. This massive undertaking aims to use 4 m diameter pipes over a length of about 4000 km to divert part of the groundwater from the southern basins to the coastal areas where most of Libya's population has settled (The Great Man-Made River Water Utilization Authority, 1996; Tarbush, 1988). It will carry 5.68 million m^3 of water per day from the southern basins to the heavily populated areas in the north: 3.68 million m^3 to the eastern conveyance system and 2 million m^3 to the western system, with 80% of its water being used for irrigation (Figure 1.5). The scheme is expected to cost around US $25 Billion, including the provision of associated agriculture and utilities infrastructure (Tarbush, 1988).

The project consists of three stages; the first (and largest) is where water produced by two well fields (Serir and Tazirbu) in southeastern Libya carry 2 million m^3 day^{-1} of water to the coastal areas extending from Ben-Ghazi to Sirt. The second stage delivers 1 million m^3 day^{-1} of water to the fertile Jeffara Plain in northwestern Libya from more than 500 wells distributed in several fields of the Murzuq Basin in southwestern Libya (Figure 1.5). The third stage comprises three parts:

- The first part conveys 1.68 million m^3 day^{-1} of water to the first phase from an additional well field within Al-Kufra-Serir Basin.
- The second and the third do not involve any additional water production. Instead, conveyance lines of the first phase (Agedabia Reservoir) will be extended farther to the east to reach Tobruq in the east of the coastal area, and farther to the west to link the Sirt Reservoir with the second phase pipelines.
- The third phase will be carried out according to the availability of adequate finance and address particular needs determined in the earlier stage. The first part will be

operational in 2010, while the first and the second phases were linked in 2000; all phases will be completed in 2015 (Schliephake, 2004).

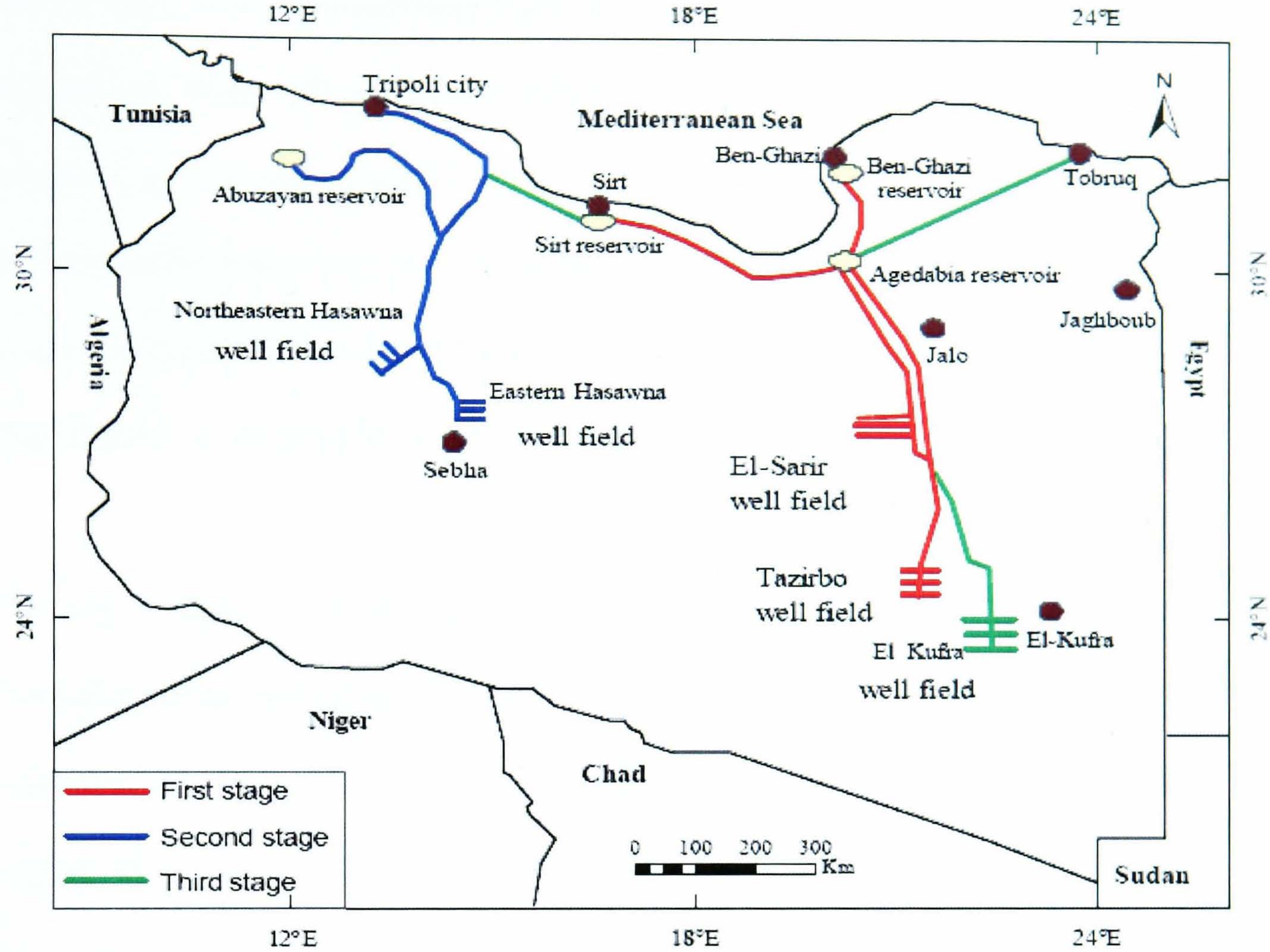

Figure 1.5. Map of the Great Man-Made River project, showing Stage I, Stage II and Stage III as the link between the first two stages. (Great Man-Made River Water Utilization Authority, 1996).

1.5. Groundwater in Libya

In the Mediterranean region, groundwater resources are either the main sources of freshwater or a vital supplement to surface water sources. Groundwater represents more than 50% of the available water resources in the Mediterranean islands and it is virtually the only water resource in the Sahara region, extending from Egypt to Morocco (EMWIS, 2005). However, groundwater supply is under threat from problems such as scarcity, which in many cases is accompanied by poor groundwater quality, especially in coastal aquifers, where the water is often highly saline, affecting both the quantity and the quality of water that the aquifers provide. Groundwater exploitation in the region has increased dramatically during the last decade, mainly due to an increase in irrigated agriculture, tourism and industry (ACSAD, 1994; Droubi, 1996; EMWIS, 2005). Thus, many groundwater resources are at risk of being exhausted through over-abstraction. With withdrawal exceeding the internally renewable water resources, the resulting groundwater scarcity is rapidly becoming a major concern in most countries of the Mediterranean region. The pressures on natural groundwater resources are higher in the summer period, when natural supply is minimal and while water demands are at a maximum (e.g. for irrigation and tourism) (EMWIS, 2005).

Libya is a mostly arid and semiarid, sparsely populated large North African country. Annual average precipitation rates are 200 mm with more than 95% of the country receiving less than 100 mm year^{-1} (Figure 1.6). Evaporation rates are among the highest in the World because of the dry climate, with temperatures exceeding 40°C in some parts of the country during a summer season. Significant improvements in the standard of living, because of Libya's vast oil wealth, have resulted in a rapid growth in both population and water consumption rates for domestic, industrial and agricultural purposes. This growth has had a marked impact on the country's water resources which have suffered serious depletions and deterioration in quality. These impacts, along with recurrent droughts and uneven population distribution, have prompted the search for non-conventional sources including large water transfer, water desalination, and wastewater recycling and reuse (Abufayed and El-Ghuel, 2001).

The highest rainfall occurs in the northern Tripoli region (Jabal Nafusah and Jeffara Plain) and in the northern Benghazi region (Jabal al Akhdar), these two areas being the only ones where the average annual rainfall exceeds the minimum value (250–300 mm year^{-1}) considered necessary to sustain rain-fed agriculture (Pallas, 1980).

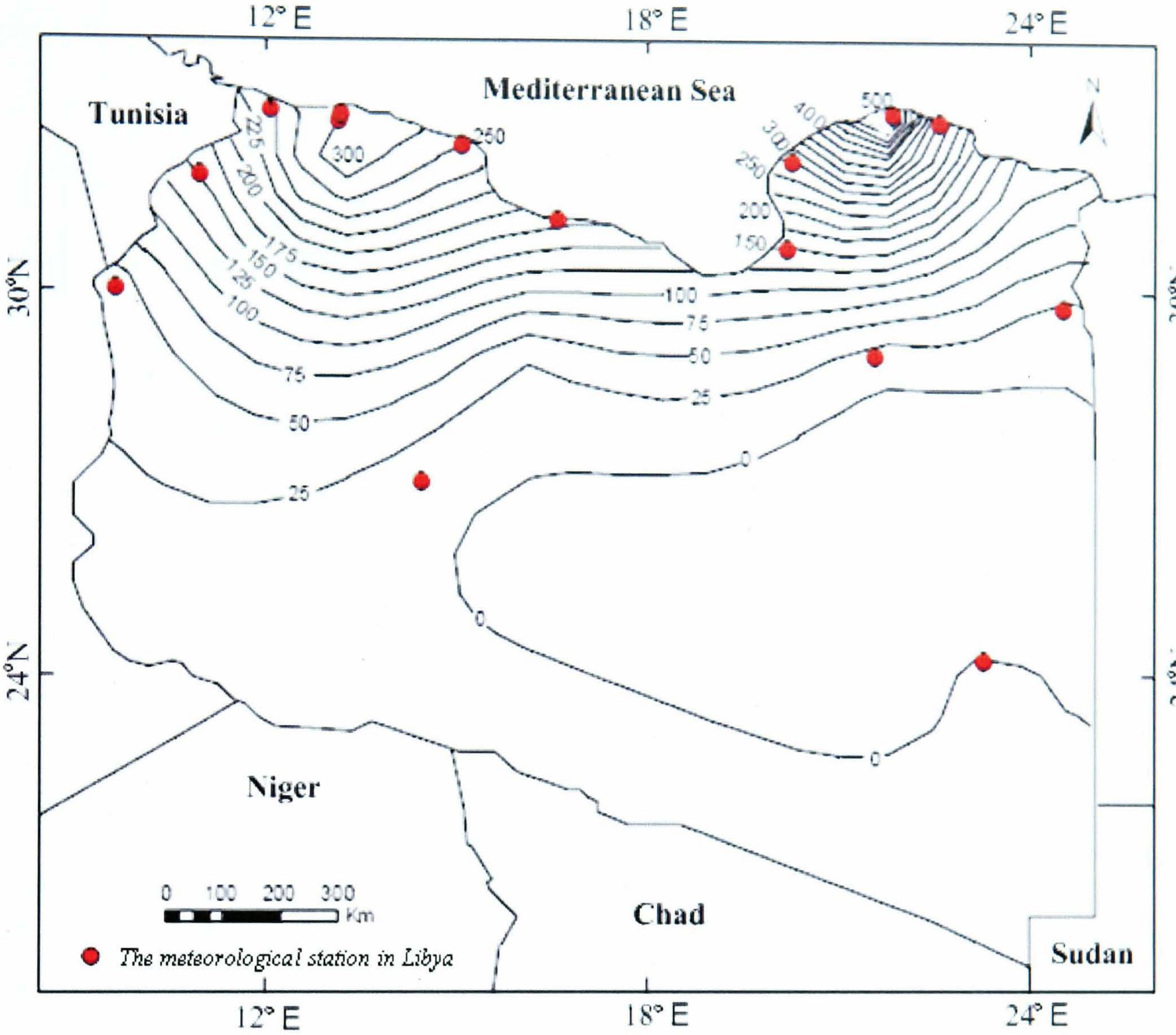

Figure 1.6. Distribution of mean annual precipitation (mm) in Libya, 1946-2000, (Libyan Meteorological Department, Tripoli).

As it has basically no renewable water resources, Libya relies heavily on groundwater for satisfying its ever-increasing water needs with minor contributions from springs, wadis, surface runoff and dams (Libyan General Water Authority) (LGWA). Because of these harsh environmental conditions, over 80% of Libya's population reside along a mild thin strip on its 1900 km long Mediterranean coast, which also contains the country's most fertile lands and its major industrial projects. Libya has no perennial rivers and is drained by intermittent water courses (wadis) that flow only after heavy rains. Most water is obtained from shallow wells that tap vast underground artesian aquifers (Pallas, 1980). Figure 1.7 shows the groundwater system in Libya. Currently, aquifers in the northern region could be recharged if sufficient input were available (i.e. rainfall): Jabal Nafusah and Jeffara Plain in the northwestern zone and Jabal al Akhdar in the northeastern zone.

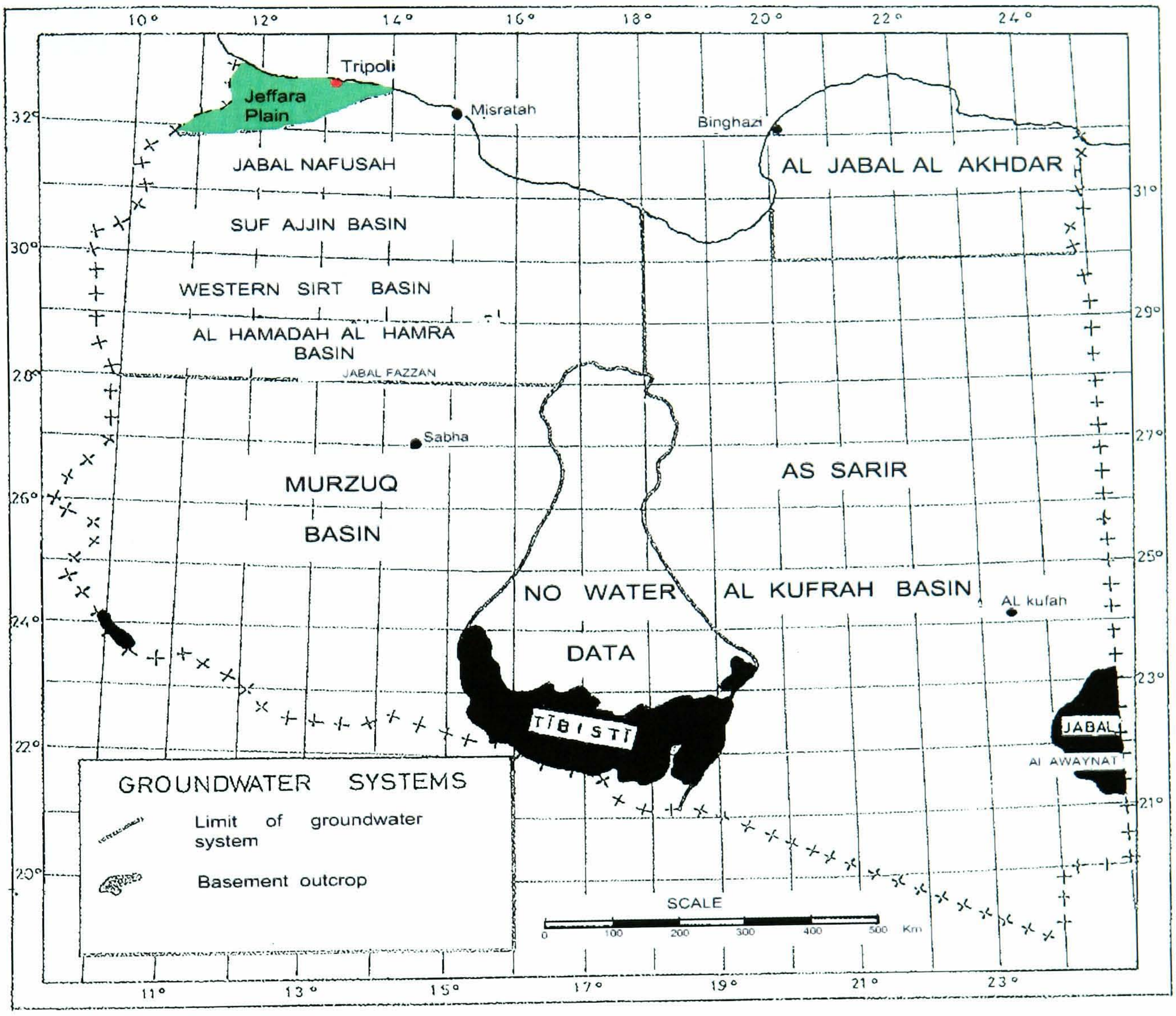

Figure 1.7. Libyan Groundwater systems. Shown are the main basins and reservoirs in Libya, (Pallas, 1980).

Renewable groundwater resources are estimated at 500×10^{6} m^{3} $year^{-1}$ (Pallas, 1980). South of 29° N latitude, an important development of Palaeozoic and Mesozoic sandstones enabled water to be stored safely during the late Quaternary, before the climate turned extremely arid. Most of the water used in Libya comes from these huge fossil reserves. Groundwater in Libya occurs mainly as part of four aquifer systems, which are relatively independent of one another. These are described in detail by Pallas (1980) and briefly introduced here. They are:

- As Sarir Al Kufrah basin system: This is in southeast Libya and forms an elongated depression oriented northeast-southwest, with an areal extent of about 400,000 km^2. The basin fill attains a maximum thickness of 2600 m.
- Sirt basin: This basin extends to the Al Kufra basin and, via a major marine embayment developed in Eocene times, to the Tibisti massif.
- Al Jabal al Akhdar system: The area considered in this section includes that part of Libya located north of 30°N latitude and west of the Egyptian border.
- The Western Aquifer system (Western Jamahiriya Aquifer System, WJS). The WJS aquifer system extends over 864,000 km^2, and includes interconnected sub-systems:

  a. The Murzuq basin is a large cratonic structure filled with deposits of Cambrian to Quaternary age with a maximum total thickness of more than 3000 m in the central part. Jabal Hasawnah is located in the Murzuq basin, which is going to play an important role in the future as a water source for the western water transport system as the source of the water for the second stage of the GMMR.

  b. The Al Hamadah Al Hamra system, including the Jabal Nafusah – Suf-Ajjin-Tawurgha sub-basin, Ghadamis sub-basin and Jeffara Plain system, aquifer occurs in the Hamada Al Hamra Al Jufrah area and corresponds to the upper aquifer in this area. The water bearing formations consist of fractured dolomitic limestones with marl, shale and gypsum of Late Cretaceous age (Pallas, 1980).

1.6. Factors impacting on groundwater

Several factors impact upon groundwater availability and quality: these include depletion; water logging and salinization; and pollution (Shah *et al.*, 2000). The depletion of groundwater levels due to high pumpage is an issue especially in regions with high population densities and irrigated agriculture with insufficient surface water. At the heart of the urban groundwater problem is population density: cities rarely have a large enough recharge area to support the needs of their inhabitants on a sustainable basis (Shah *et al.,* 2000). The increase in groundwater salinity, particularly in coastal areas, may be due to the influx of natural saline water, such as sea water intrusion, dissolution of soluble salts in the unsaturated zone, or the flow of saline water from adjacent aquifers. Anthropogenic contamination is another major cause of salinization and water-quality degradation. Another problem affecting groundwater is pollution; however, the most important source of diffuse pollution comes from agricultural practices in irrigated areas (Candela *et al.*, 2008; Mahvi *et al.,* 2005). One of its most pronounced impacts is an increase in the nitrate concentration, which is derived from infiltration of sewage effluents, industrial wastes and agriculture return flows (Kass *et al.*, 2004). Direct groundwater recharge by rainfall affects groundwater quality and development in many regions of the World. Factors affecting such recharge include: type, amount and distribution of precipitation; initial soil moisture content; soil infiltration characteristics; topography; and vegetation cover (Hussein, 2001).

Vegetation plays a key role in the interactions between groundwater and surface-water systems, because of its direct and indirect influence on recharge and because of the dependence of vegetation communities on groundwater (Le Maitre *et al.,* 1999). Changes in vegetation cover and structure, particularly from low vegetation such as grassland to tall vegetation such as forests, can have a significant impact on groundwater recharge by altering components of the hydrological cycle, such as interception and transpiration. In South Africa, for example, the impacts of vegetation changes on base flow and/or groundwater have been documented in both humid and sub-humid catchments but the greatest changes in groundwater levels have followed vegetation type conversions in semi-arid savannas and on the coastal plains of Zululand (Le Maitre *et al.,* 1999).

1.7. Land cover effects caused by groundwater changes

Groundwater systems respond to temporal variations in climate. However, the relatively slow response of many groundwater systems tends to reflect much more the low-frequency "climate" signal than the high-frequency "weather" fluctuations (Committee on Hydrologic Science, 2004). In arid and semi-arid regions, groundwater is an important source for the growth of natural vegetation, with any shortage having a serious effect on productively and biodiversity (Munoz-Reinoso, 2001; Xu *et al.*, 2007). There have been a few studies on the effects of the artificial lowering of the water table on plants and vegetation communities where it has been suggested that the availability of groundwater may influence the type of plant growth (e.g. shrubs or trees) as well as the species assemblages (Xu *et al.*, 2007). Furthermore, interactions between groundwater and vegetation appear to be generally more important than was believed in the past (Le Maitre *et al.,* 1999). A study by Xu *et al.* (2007) on the Tarim River, which flows through the Taklimakan desert, confirmed the positive relationship between the depth of groundwater and natural vegetation, with the total cover of vegetation being negatively affected by reduced groundwater availability.

In a further example, Brooks *et al.* (2001) studied the effects of falling groundwater levels in Wadi al-Ajal, in the Fazzan region located in southern Libya. They noted that changes in groundwater availability and/or quality led to changing vegetation patterns in the region, with palm forests dying and reducing in extent (Figure 1.8) in certain un-irrigated locations, while tamarisk appeared relatively unaffected (Brooks *et al.*, 2001). Water table depletion can cause different effects such as: reduction and/or drying up of springs; low stream flow; diminution of soil humidity to an extent to which phreatophitic vegetation cannot survive; and changes in microclimate because of a decrease in evapotranspiration (Llamas, 2004).

Figure 1.8. Photograph of dead palm forest surrounding the medieval town of Old Germa, (Wadi al-Ajal) as a result of groundwater depletion (Brooks et al., 2001).

Excessive pumping of groundwater is an important mechanism causing land subsidence, as a result of drawdown of the water table in the aquifer, a decrease in pore water pressure and an increase of effective stress in the ground. There is a strong positive relationship between the rate of net groundwater pumping and the rate of land subsidence (Chai *et al.,* 2004). Therefore, intensive groundwater use can result not only in aquifer depletion and water quality deterioration, but can also impact on the ecological integrity of streams and wetlands, and can result in significant losses of habitat and biodiversity (Sophocleous, 2001).

1.8. Purpose and objectives

The main aim of the project is to characterise land cover change (particularly agricultural activities) from 1988 to 2000 in the Jeffara Plain, the study area of north western Libya (see Chapter 3) and determine the extent to which these are associated with changes in groundwater status (availability and quality). A subsidiary aim is to test approaches of detecting land cover/use change in this region with remotely sensed data. To achieve both of these, the following objectives have been defined:

1. To identify the surface effects of groundwater lowering with respect to land cover change characterisation (particularly agricultural activities) in the study area from field observations, literature and questionnaire surveys.
2. To determine the nature of any relationship between changes in land cover characterisation and groundwater changes in the study area as perceived by local farmers.
3. To identify and test appropriate remote sensing methods to detect and monitor the land cover change characterisation over time, including a comparison of image classification results from two different classification methods.
4. To establish the relationship between groundwater changes and the changes in the land cover/use classes (particularly agricultural activities) observed from remote sensing in the study area compared with the literature and questionnaire surveys responses.
5. To describe the pattern of land cover/use change characterisation in the study area from 1988-2000 and comment upon future implications of groundwater change and its associated impacts upon land cover/use in the region.

1.9. Project plan

The steps below and as shown in Figure 1.9 were followed to investigate the objectives of this project:

- Pre-processing of remotely sensed imagery, as multitemporal data (e.g. atmospheric correction and geometric correction).
- Field visit to check the primary classification results and to check the geometric correction of the images.
- Questionnaire survey and informal interviews with farmers who reside in the study area to link the land cover changes with the groundwater changes, and collect information related to the vegetation cover and agricultural activities in the area.
- Identification of the land cover change during the period 1889-2000 (available remotely sensed data) using maximum likelihood supervised classification.
- Accuracy assessment as an important stage of process in remote sensing applications has been carried out to assess the classified images.
- Comparison of the ML classification results as the main method used to identify the land cover changes with another image classification technique. The ANN technique was applied since most researchers agree in the literature that the ANN method is more accurate than the ML method.
- Analysing the relationship between the land cover changes (particularly agricultural activities) and groundwater changes.

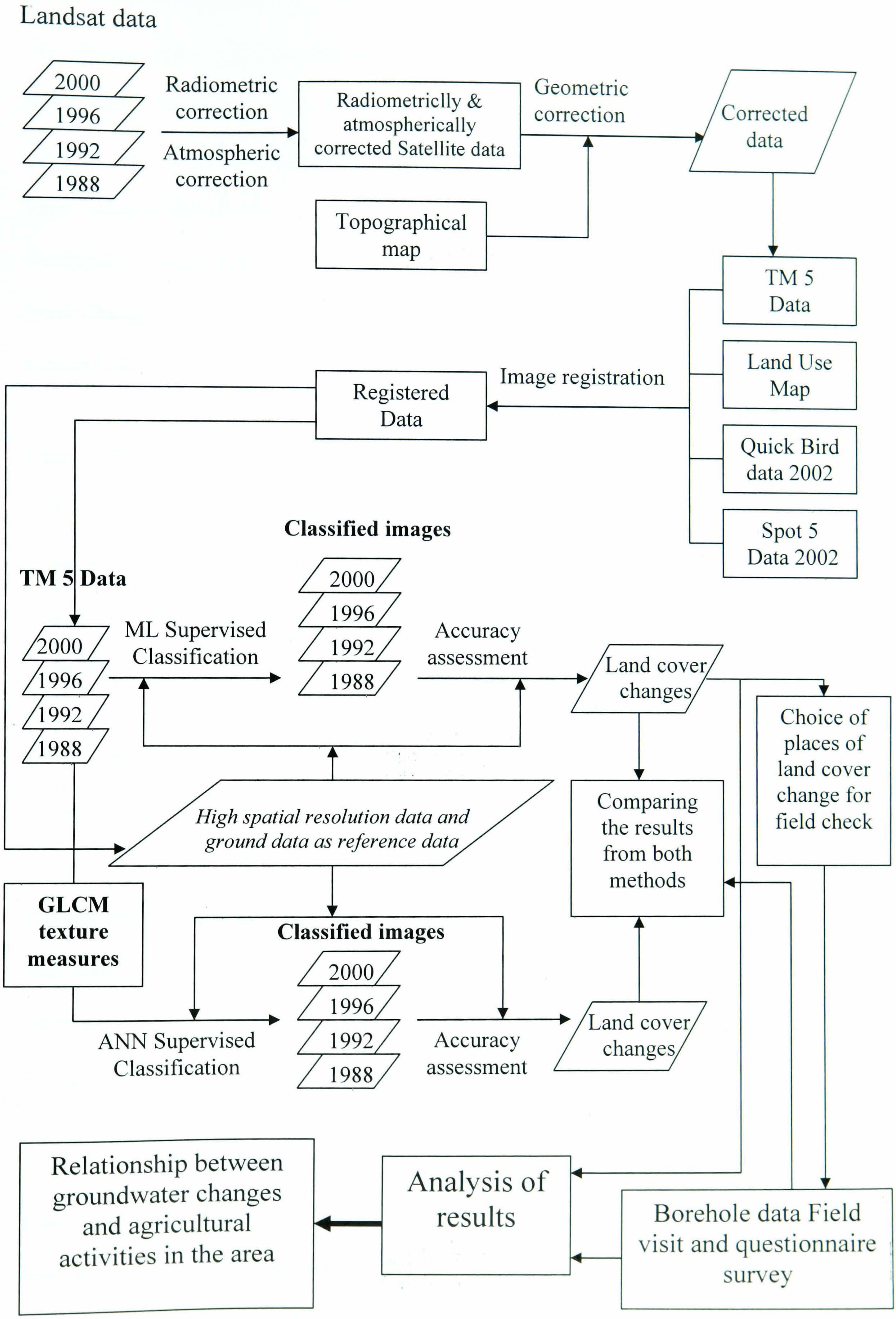

Figure 1.9. Schematic representation of the project plan.

1.10. Thesis structure

This thesis contains eight chapters, which cover three parts of the research conducted in these main areas: Firstly, the hydrology and water resource situation in Libya is presented and reviewed. Secondly, the link between groundwater changes and how these changes impact the agricultural activities is assessed by using questionnaire survey and informal interviews. Finally, remotely sensed data are used to detect the land cover changes caused by the groundwater changes, using two different methods for comparison.

Chapter Two provides a review of previous studies that have used remote sensing to monitor groundwater and its impact, and also studies which have analyzed land cover changes using multispectral and multitemporal remotely sensed data, including a description of two different remote sensing classification approaches that are used later in the thesis.

Chapter Three offers an overview of the aquifers and groundwater situation in Libya and present characteristics of the study area as part of the Jeffara Plain and.

Chapter Four the chapter presents the all data used in this project (hydrological data, field data, questionnaires survey and imagery data), with the steps of pre-processing which applied to prepare the multi-temporal data used to detect the land cover changes. The preparation of the questionnaire survey preparation and the field visit are also explained in this chapter.

Chapter Five introduces the questionnaires survey results, attempting to elucidate the relationship between groundwater conditions and the change in agricultural land cover in the area. In addition, examples of possible surface effects of groundwater change in the area are described.

Chapter Six presents the results of the maximum likelihood (ML) supervised classification analysis to detect land cover changes in the area. The results focus on changes characterization particularly in the vegetation cover classes that have likely been affected by the changes in the groundwater status.

Chapter Seven describes the use of an artificial neural network (ANN) classification as an alternative method to compare the results with the ML analysis. A comparison of both results observed and methods is made, with analysis of the impacts upon relationships observed.

Chapter Eight discusses the changes in the land cover/use patterns which were detected over time through remote sensing by different methods of image classification, and assesses the relationship between these changes and groundwater status change in the region.

Chapter Nine concludes the study within a discussion of the importance of groundwater in arid and semi-arid areas and how changes in groundwater might affect the land cover (agricultural activities) as detected through multitemporal remote sensing techniques. This chapter also presents the key findings and recommendations for future work.

Appendices provide information about the data used in the project, as well as a copy of the questionnaire survey (in both English and Arabic).

Appendix (I) Borehole data (groundwater depth)

Appendix (II-A) Table prepared for the field visit contain.

CHAPTER TWO

Remote sensing of land cover and groundwater

2.1. Introduction

One of the likely effects of unchecked groundwater availability and changes (availability and quality) is environmental degradation, which affects the vegetation cover (semi-natural and managed), soil properties and ultimately patterns of land cover occurring on the Earth's surface (Yuan *et al.*, 2005). As a result, this review will focus on remote sensing methods to detect these changes.

The term remote sensing refers to obtaining information about an object without being in physical contact with it (Lillesand *et al.*, 2004). Many different airborne and space-borne platforms have been or are currently used for the acquisition of remotely sensed data. Most of these platforms are equipped with instruments that allow data to be collected simultaneously from different parts of the electromagnetic spectrum on a systematic and repeated basis. These multispectral data can be analysed to determine certain characteristics of the objects areas under study including the land cover. Remote sensing is also useful in identifying temporal change by using images of a different date covering the same region (Eslick, 2000).

During the last three decades, methods of remote sensing and its technologies have evolved dramatically to include a suite of sensors operating at a wide range of imaging scales (both temporal and spatial) with interest and promise to revolutionize land management by delivering spatial information critical for Earth surface characterization (Rogan and Chen, 2004). Data from satellite remote sensing have been commonly applied to a wide range of research problems and practical applications. However, the most important fields of applications are: meteorology, canopy and soil investigations, agriculture and crop production, water, ice and ocean research and management, geology, land use and environment monitoring, reconnaissance and defence (Ferencz *et al.*, 2004). Major resources have been provided for these tasks, exemplified by the launch of seven Landsat satellites, numerous airborne and space-based sensors using multiangle, multispectral and radar techniques, the creation of several global land cover databases, and through research attempting to demonstrate the efficacy of a predominantly remote sensing and GIS based approach to land management (Coppin *et al.,* 2003; Saraf, 2004).

2.2. Remote sensing of groundwater

Remote sensing has been widely used to identify the characteristics of the surface of the Earth (e.g. lineaments, and geology) which can then used to infer the presence of aquifers and groundwater availability and recharge (Sener *et al.,* 2005). However, directly mapping the effects of groundwater change has received less attention but is no less important given the increased demand for water. Several studies have documented that there are negative effects of hydrological alterations on vegetation (Nilsson and Berggren, 2000; Vandersande *et al.*, 2001). Remotely sensed data provide a wealth of readily available data for regional analyses of vegetation (Tueller, 1987) and so should be able to record changes associated with changing groundwater conditions. For example, Elmore *et al.* (2003) used remotely sensed measurements of vegetation live cover for an entire water management area in Owens Valley, Eastern California. Landsat TM data, field observations, precipitation records, and data on water table depth were used to quantify and describe the role of groundwater decline and climatic variability on live cover of semiarid vegetation. Landsat TM images were acquired during September of each years, 1986 -1998, and then classified to locate the change in the vegetation cover using unsupervised classification, results illustrate there is a relationship between the groundwater decline and vegetation cover such as phreatophytic grasses and shrubs. For example the life form dominance represents a change in the function of the ecosystem from place drought by groundwater availability and other sensitive to small variations in precipitation. Also note that the live cover and plant community function was sustained in regions of phreatophytic vegetation where the depth to water did not change despite a regional drought. The patterns of vegetation change were then integrated with the other data to determine the source of that change.

Remote sensing and GIS tools are playing a rapidly increasing role in the field of hydrology and water resources development generally (Saraf and Choudhury, 1998). GIS provides an illustration of the spatial features of the Earth, while hydrological modelling is concerned with the flow of water and its constituents over the land surface and in the subsurface environment. These tools, combined with remotely sensed data are providing new decision support systems and allow convergent analysis of spatial data from diverse sources (Saraf *et al.,* 2004).

For example, Yeh *et al.*, (2008) applied remote sensing and GIS techniques to integrate five contributing factors to groundwater recharge: lithology, land cover/land use, lineaments, drainage, and slope in Chih-Pen Creek basin in eastern Taiwan. The weights of factors contributing to groundwater recharge were derived using aerial photos, geological maps, a land use database, and were verified with field observations. They produce a groundwater recharge potential map of the study area and show the most effective groundwater recharge potential zone. The study showed that remote sensing and GIS are effective for hydrological researches.

2.3. Remote sensing of vegetation change

A progressive degradation (desertification) of vegetation cover can be distinguished in many regions of the planet using remote sensing. This degradation is particularly clear in the Mediterranean basin (Sanchez-Diaz, 1994, cited in Camacho-De Coca *et al.*, 2004) where many factors promote this process, such as the decrease in water resources and the progressive degradation of soil (e.g. due to overgrazing or forest fires). Remote sensing is an effective tool for observing the abundance, distribution and evolution of the vegetation cover, which can be considered as an indicator of land degradation (Camacho-De Coca *et al.*, 2004).

Multitemporal images, taken over the same area over a period of time, can reflect changes in vegetation cover. Remote sensing is also an excellent tool for monitoring changes in vegetation composition and detecting signs of development and erosion (Goldberg *et al.*, 1999). For example, Levien *et al.* (1998) describe how Landsat TM satellite imagery of different dates over the state of California have been used as part of a long-term, low cost monitoring programme to identify trends in forest health, assess changes in vegetation extent and composition, and provide data for updating regional vegetation and fire perimeter maps. In addition, satellite remote sensing has proved effective for the purpose of mapping vegetation cover types, using either classification of multispectral data at a single point in time for relatively small areas at fine spatial resolution (e.g. Mehner *et al.,* 2004) or multitemporal data for large areas at a relatively coarse spatial resolution, with the capability to resolve vegetation successional stages and land use change (e.g. Coops and Waring, 2001).

2.3.1. Spectral properties of soil and vegetation

In arid and semi-arid areas soil and vegetation are the dominant land cover types, i.e. bare soil being much more visible than in temperate regions. The extraction of vegetation boundaries from the satellite image is based primarily on its spectral, spatial and radiometric resolution that forms the basis of a spectral signature (Lilliesand and Kiefer, 1994). Much attention in the remote sensing of green vegetation is focused on the strong reflectance contrast between the visible and the near infrared (NIR) which forms a strong step in the spectrum of green vegetation and is often referred to as the "red edge" of plant reflectance (Horler *et al.*, 1983). Figure 2.1 illustrates the spectral reflectance curve for green vegetation, dry bare soil and water. In the visible bands (0.4-0.7μm) absorption of light due to plant pigments strongly dominates the reflectance spectra. Chlorophyll, for example, strongly absorbs energy in the wavelength bands centred at about 0.45 and 0.67 μm (Lilliesand and Kiefer, 1994). On the other hand, the spectrum of soil is plotted for comparison to that of vegetation to illustrate that change in reflectance between the visible and the near-infrared is much smaller for soil than for green vegetation (Sabins, 1997).

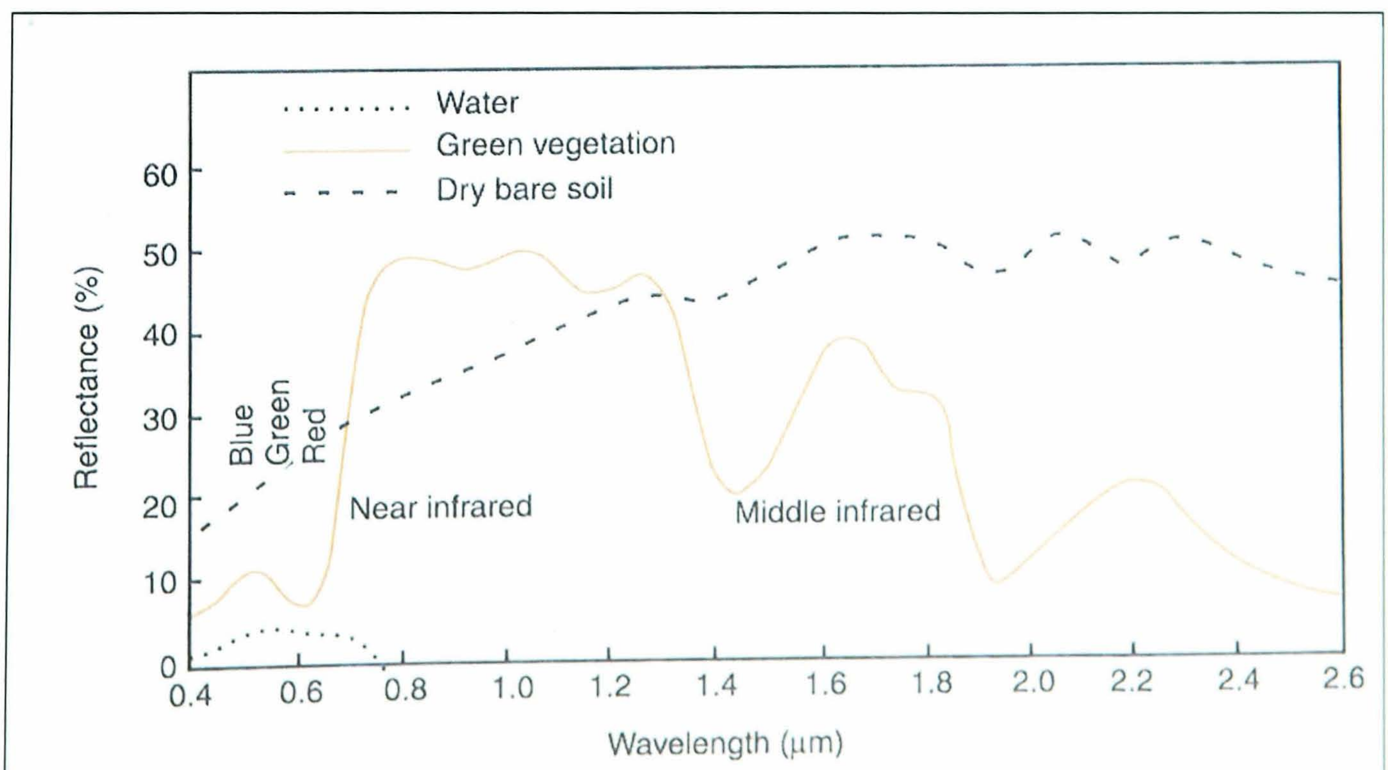

Figure 2.1. Green vegetation and soil and water spectra for the wavelength range 0.4-2.6 μm (Sabins, 1997).

Significant relationships between soil properties and the spectral reflectance of soil in the visible and near-infrared portions of the electromagnetic spectrum show that it is possible to use remote sensing techniques to quantify soil properties (Stoner and Baumgardner, 1981). Soil properties have been inferred from reflectance measurements made under laboratory conditions and *in situ*, including estimates of moisture, organic carbon, total nitrogen, and other chemical properties and minerals (e.g. Ben-Dor and Banin, 1994; Dalal and Henry, 1986; McMorrow *et al.*, 2004).

Karnieli *et al.* (2002) state that the spectral response of soil and vegetation in the visible and near infrared (NIR) is probably the most popular subject for research among remote sensing scientists. Despite much research in this field, there remain several challenges in detecting and monitoring vegetation using multispectral imagery from airborne or spaceborne sensors. These challenges are, firstly, assessing temporal change in the phenological (growth) stage of plants (Fischer, 1994); secondly, the extraction of temporal change in the soil/rock background signature (Eldridge and Greene, 1994) and finally, the discrimination of vegetation from a soil or rock background, where the spectral signature contains a mixture of the vegetation, which characterizes the above-ground cover, and the underlying material. Various studies have shown that when the dispersed plant cover is less than 30-40%, satellite sensors are not capable of detecting vegetation, and the signal received represents mostly the soil background (Huete *et al.*, 1984; Smith *et al.*, 1990; Tueller, 1987).

2.4. Change detection methods

As human and natural forces continue to alter the landscape, different communities are finding it increasingly important to develop monitoring methods to measure these changes. Remote sensing provides a viable source of data from which updated land cover information can be extracted efficiently and cheaply in order to provide an inventory and monitor changes effectively (Dai and Khorram, 1998). Because of repetitive coverage at short time intervals and consistent image quality, remotely sensed data, such as Thematic Mapper (TM), Satellite Probatoire d'Observations de la Terre (SPOT), radar and Advanced Very High Resolution Radiometer (AVHRR), have become the major data sources for different change detection applications during the past decades (Lu *et al.*, 2004). The type of remote sensing data to be select depends on the objectives and requirement of specific project and data available in the study area. The high resolution of Landsat makes this satellite highly valuable for agricultural and water resources management, where reflective and thermal information can be retrieved for individual agricultural fields. In addition, Landsat satellite TM have three bands in the visible domain and one in the near-infrared part of the electromagnetic spectrum, which enable the estimation of land use/land cover patterns, also TM data is often used as a middle-level resolution for a local area (Lu *et al.*, 2004). Therefore TM data was used in this research.

The basic premise in using remote sensing data for change detection is that changes in land cover result in changes in radiance values (i.e. the spectral response), and that changes in radiance due to land cover changes are large with respect to radiance changes caused by others factors, such as differences in atmospheric conditions, differences in soil moisture and changing solar angles (Roy *et al.*, 1991; Sader *et al.*, 1991). Changes in vegetation result in changes in wildlife habitat, fire conditions, aesthetic and historical values, ambient air quality, and other resource values, which in turn influence policy decisions (Levien *et al.*, 1999). To detect such changes, satellite images must be co-registered and radiometrically corrected. Image registration ensures that multi-date images from the same path and row are registered to each other within one pixel by on-screen identification of common features, such as road intersections, and if pixels do not correspond correctly, then changes due to misregistration will occur on the final change map (Labovitz and Marvin 1986), therefore it has a significant effect on the accuracy of remotely sensed change detection (Dai and Khorram, 1998). Several studies have investigated the bias potential of false change detection due to positional error. For example, Townshend *et al.*, (1992) and Dai and Khorram (1998) clearly demonstrated that, to achieve the change errors and detect 90% of true change using multi-temporal Landsat TM images, a co-registration accuracy of less than 0.2 pixel may be required.

Differences in atmospheric conditions at the time each image was acquired also affect the pixel values in each image. Consequently, to correct for these differences, all images must be radiometrically corrected or normalized to each other. One approach is to extract invariant light (rock outcrops) and dark (water bodies) features from both dates of imagery and apply a regression-based correction (Levien *et al.*, 1998). Other types of radiometric corrections include absolute correction and relative correction from both radiation transfer modelling and image based methods; these types are commonly employed to normalize remotely sensed images for time-series comparison. In fact, absolute radiometric correction aims to extract the absolute reflectance of scene targets at the surface of the Earth (Chavez, 1996; Song *et al.*, 2001), but in reality is rarely applied due to lack of concurrent meteorological data being routinely available (Chen *et al.*, 2005). The relative correction was used in this research as the metrological data not available.

Multispectral sensors collect data in a few broad wavebands which cover important regions of the reflected solar spectrum (about 350-2500 nm). There are numerous sensors providing multispectral data regularly with different spatial, spectral, temporal and radiometric resolutions (e.g. NOAA AVHRR, Landsat TM, and SPOT HRV to name but a few). The capabilities of providing systematic multispectral and multitemporal data offer the possibility to use these data to identify changes on the surface of the Earth.

2.4.1. Techniques for vegetation change detection

The main purpose of this project is to identify the impact of groundwater on agricultural activities, where the important classes of agricultural activities are vegetation classes. Many techniques have been used to detect change in vegetation status, extent and properties using satellite data. Most digital change detection methods are based on per-pixel classifiers and pixel-based change information contained in the spectral domain of the image (Coppin *et al.*, 2004). There are various different change detection algorithms that have been used to monitor vegetation canopies, including:

a. Classification comparison (also called post-classification comparison). This involves producing separate spectral classification results for different images, followed by pixel by pixel or segment by segment comparison to detect the change in the land cover type. The accuracy of the change observed is dependent on the accuracy of the initial classifications. Many studies have used a classification comparison approach (e.g. Hall *et al.*, 1991; Xu and Young, 1990; Oetter *et al.* (2000), Shrivastava and Gebelein (2007)). For example, Yuan *et al.* (2005), developed a methodology to map and monitor land cover change using multitemporal Landsat Thematic Mapper (TM) data in Minnesota. The overall accuracy of land cover change maps generated from post-classification change detection ranged from 80% to 90%.

b. Vegetation indices (VIs) and spectral mixture analysis (SMA) are most frequently used in remote sensing to estimate the amount of vegetation (Camacho-De Coca *et al.*, 2004) present. Vegetation indices are often calculated from the reflectance values in the red (R) and near infrared (NIR) wavebands. The most commonly used vegetation index is the Normalized Difference Vegetation Index (NDVI) which has a high correlation at local scale with various plant parameters, such as leaf area index (Wiegand *et al.*, 1979; Curran *et al.*, 1983), Chlorophyll content (Chappelle *et al.*, 1992), and crop condition (Wiegand *et al.*, 1992).

c. Image enhancement: this approach involves the mathematical combination of imagery from different dates, including subtraction of bands, image regression, principal components analysis, and image ratioing. For example, image ratioing is one of the conceptually easier to understand change detection methods (Coppin *et al.,* 2004) as the data are ratioed on a pixel by pixel basis. Data which have no change will yield a value of one but pixels from areas that have changed will have a value either higher or lower than one.

d. Multi-temporal Kauth-Thomas (MKT) transform (Kauth and Thomas, 1976): this method detects change using a linear transformation that reduces several TM bands into brightness, greenness and wetness components. This does, however, require extremely accurate radiometric and atmospheric correction to ensure that the pixel values represent real change on the ground and not a change in the environmental conditions under which the data were collected (Levien *et al.*, 1989).

Mas (1999) tested six different techniques of change detection using Landsat Multi-Spectral Scanner (MSS) images over the region of the Terminos Lagoon, a coastal zone of the State of Campeche, Mexico. Those considered were image differencing, vegetation index differencing, selective principal components analysis (SPCA), direct multi-data unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison. The accuracy of each result was evaluated by comparison with aerial photography and through Kappa coefficient calculation. The most accurate procedure was judged to be post-classification analysis which also had the advantage of indicating the nature of the changes that had occurred. In addition, the image enhancement procedures were not able to determine accurately the variation in soil moisture and vegetation resulting from the land cover changes, while the classification techniques avoided this problem.

2.5. Image classification

The classification of remotely sensed data (i.e. segmentation of pixels into classes of interest) is being used increasingly to produce thematic land cover maps (Foody, 2002). Image classification in remote sensing can be performed in several ways, e.g. supervised or unsupervised, parametric or nonparametric, contextual or noncontexual. In this project the supervised classification is the method used to characterise the change in the land cover.

2.5.1. Supervised classification

Supervised classification methods depend upon the input of knowledge of the area which has to be classified. Methods are applied using either statistical or neural approaches. Statistical algorithms utilize parameters derived from sample data in the form of training sets, such as the minimum and maximum values, mean and covariance features. Neural algorithms do not use statistical information from data samples but use the samples to train the classifier directly (Mather, 2004).

2.5.1.1. Statistical supervised classifiers

Statistical classifiers require land cover classes to be specified initially to determine the statistical characteristics for each class (Mather, 2004). There are a number of algorithms available, including the Maximum Likelihood (ML) which is used in this project. This and other algorithms are comprehensively reviewed by Mather (2004) but a brief introduction is presented here. Maximum Likelihood is a parametric classifier based on the assumption of a multivariate and normal distribution of the data to be classified (Mather, 2004). The algorithm considers the relative likelihood of overlapping pixels using the training data as a means of estimating class variances and also using the variability of brightness of each class to maximize the probability of correct classification (Campbell, 2006). The training sample data used in the ML also provide extra information such as the shape of the distribution of the members of each class as well as the location of the centre of each cluster; therefore, the resulting classification might be expected to yield a more accurate result than those produced by the other statistical supervised classifiers (Mather, 2004).

Maximum Likelihood is commonly used as a hard classifier in that each pixel is treated as statistically independent and allocated to a single class only. This is one of the traditional parametric approaches widely applied to the supervised classification of remotely sensed data (Richards, 1993; Mclver and Friedl, 2002).

2.5.1.2. Artificial neural network classification (ANNs)

As an alternative to statistical/parametric approaches of image classification, neural methods have recently been developed as non-parametric methods in an attempt to address some of the limitations seen with techniques such as ML. ANNs are an artificial intelligence technique designed to simulate the perceived working of the human brain in terms of the ability to learn and generalise, i.e. the ability to manage and process data (Mather 2004; Openshaw, 1997). A network is trained by process or learning by example and experience. Neurons in a human brain receive inputs from other neurons and produce an output, which are then passed to other neurons (Atkinson and Tatnall, 1997). With ANNs, a node is the basic element (Figure 2.2), which mimics the biological neuron and carries out two particular functions. The first process sums the values of its input (a function of the input data and weights attained to each link in the network) (Paolo and Schowengerdt, 1995).

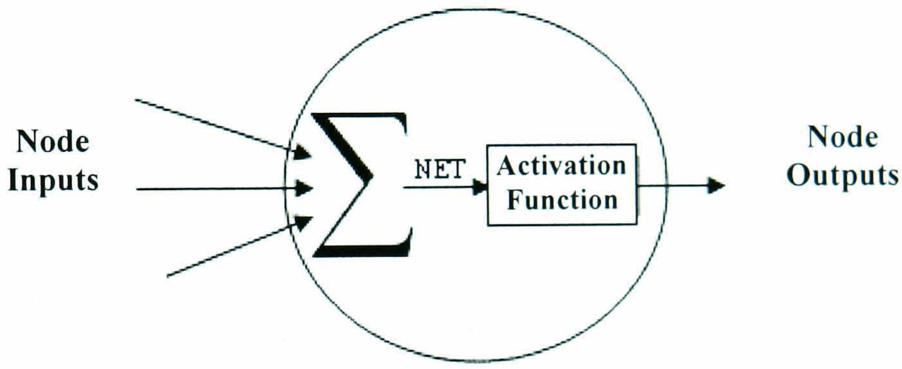

Figure 2.2. Internal structure of a neural network processing node.

This sum is then passed through an activation function to produce an output. Nodes are organized into layers and each layer is fully interconnected to the following layer. Data are then presented to the network and training taken place according to the type of network used. The most commonly used network in remote sensing is the multi-layer perceptron (MLP).

During the last decade the use of neural networks for various applications of remote sensing has increased progressively (Atkinson and Tatnall, 1997). In particular ANNs have often been applied to the classification of remotely sensed images, (Li, 1998; Mas and Flores, 2008). There are many advantages of neural classifiers. For example, the network learns from the relationship between the inputs and the output. In addition, ANNs are able to deal with incomplete information, because of the ability to generalize in noisy environments, which is useful in the presence of incomplete or imprecise data (Hewitson and Crane, 1994); it can also deal with different kinds of data (in terms of measurement scale) and use it as input data. This is something that statistical classifiers are unable to deal with as they assume the data are of the same measurement scale and free from noise (Foody *et al.*, 1992).

Whilst ANNs have been shown to be useful for classifying remotely sensed data, there are a number of limitations that have also been previously identified:

- The ANN is a black box technology (Openshaw, 1997);
- The technique is not easy to learn and understand;
- The design of the network is subjective (Mather, 2004);
- It can take a long time to train a method with difficulty in determining whether it has been trained sufficiently (Mather, 2004);
- There is a demand for a large amount of training and testing data.

2.5.1.2.1. Multi Layer Perceptrons

The Multi Layer Perceptron (MLP) network model is one of the most widely used neural networks applied to classify remotely sensed data (Atkinson and Tatnall, 1997; Hepner *et al.*, 1990). MLPs are trained using the back-propagation algorithm and usually consist of three or more types of layers: an input layer, an output layer and one or more hidden layers (Figure 2.3). Each layer consists of processing nodes that are fully connected to each other, except that there are no connections between nodes within the same layer. The input layer nodes correspond to individual data sources, such as wavebands in a remotely sensed image. As extra input data some researchers have used textural features combined with spectral information for land cover mapping with positive results (Berberoglu *et al.* 2000; Puissant *et al* 2005). The features used to describe the texture can be obtained by several methods.

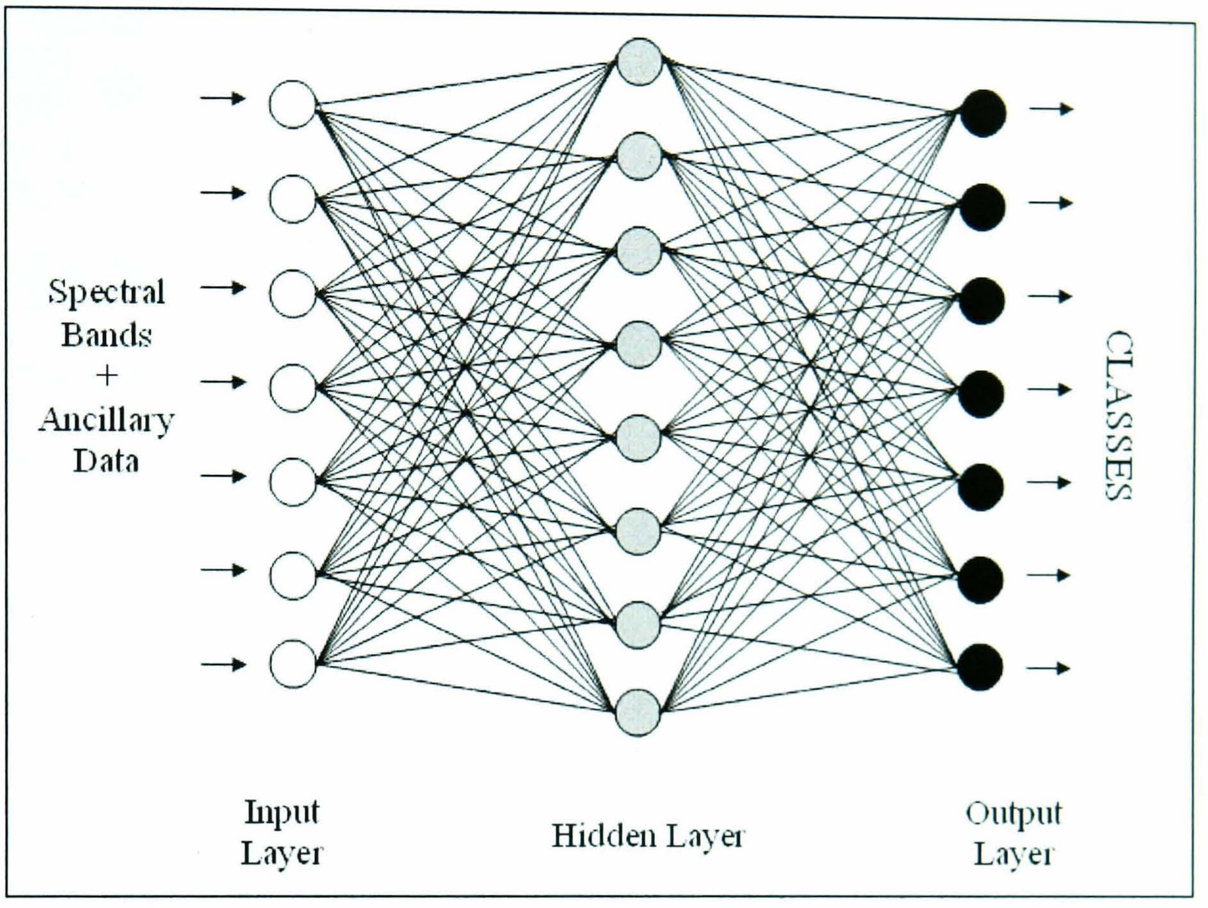

Figure 2.3. Multi Layer Perceptrons (MLPs) feed-forward neural network.

The most traditional are statistical approaches, which are based on the measurement of the occurrences of each grey level value in a particular neighbourhood as described by Haralick *et al.* (1973). Other methods are available for describing the texture at different scales and decomposing an image into a pyramid of scale an orientation bands (Simonceli and Freeman 1995). Aksoy and Haralick, 1998 used the grey level co-occurrence matrix (GLCM) for retrieval of images similar to an input image, achieving high percentage accuracy. Hidden layers are used for computations, and the values associated with each node are estimated from the sum of the multiplications between input node values and weights located on the links connected to that node. The final layer is the output layer which includes a set of nodes that represent the classes to be recognised.

Backpropagation is also referred to as feed forward training, where data are presented to the network and then forward (multiplied by weights on each link), whereupon they are processed by a node in the hidden layer. The output from these nodes is then fed to the output layer where it is compared to the actual value (described in the training data) and the magnitude of error between the two is used to adjust the weights on each link. The data are then 'fed' through the network once again and the new error computed once more. By iterations, the network 'learns' that a particular set of input values (spectral response) represents the desirable output in terms of being validated by an independent training set, before the network is then used to classify the entire image.

The algorithm has been used successfully in change detection and mapping studies (e.g. Gopal and Woodcock, 1996) as well as for land cover classification (Aitkenhead and Wright, 2004; Atkinson *et al.*, 1997; Foody *et al.*, 1997; Jarvis and Stuart *et al.*, 1995; Kavzoglu and Mather, 2003; Mendoza *et al.*, 2004; Pal and Mather, 2003; and Tatem *et al.*, 2002).

2.5.2. Training data

Both methods (statistical/neural) require a step known as 'training', where pixels of known class membership are used to train either a statistical or neural classifier. Training datasets comprise a series of pixels of known class membership from the digital image to be classified. A key consideration is the number of pixels selected for each class. The location of the training datasets is also important, and consequently each class should be represented by several training datasets that are positioned throughout the image (Campbell, 2006). A number of training sets is required to minimize spatial autocorrelation and to capture all within-class variance which is affected by the number of bands. The representations and validity of training samples as the source of information for the classes present in the image are one of the issues which control the classification accuracy (Mather, 2004). Also, the size of the training set has an influence on resulting accuracies (Foody *et al.,* 1995; Foody and Mather, 2004). If the training sets are too small, the class probability density function will not have enough precision to accurately estimate the features (i.e. complex features) (Van Niel *et al.,* 2005). Therefore, small training sets may sometimes represent a major problem to classification analysis, with poor classification accuracy resulting from not characterising the class variability sufficiently (Jackson and Landgrebe, 2002). The aim of the training stage is to define an accurate spectral model of the classes (Campbell, 2006). Therefore, the training sample should provide a full representative description of the classes contained within the image or area of interest (Chen and Stow, 2002; Lillesand *et al.,* 2004).

2.6. Summary

Remote sensing is a useful tool for monitoring changes in vegetation composition. Remote sensing provides a wide range scale and can save time, money (Sener *et al.,* 2005) and effort in performing initial surveys or monitoring studies. It can, depending on the resolution and type of equipment used, be an effective way of conducting a study with results better or as good as more traditional techniques (Lillesand *et al.,* 2004). Analysis of the spectral response of soil/rock and vegetation in the visible and NIR is the most commonly used technique for discriminating different land cover classes. However, monitoring and detecting vegetation using multispectral imagery is complicated by several difficulties, including the effects of background soil which can make detecting change difficult. Commonly used methods for multi-temporal analysis include multi-temporal post-classification analysis and time series NDVI. Several studies have compared image classification results from neural classifiers against statistical parametric classifiers (e.g. maximum likelihood), with most reporting that using ANN produces considerably better results with higher accuracy (Foody *et al.*, 1992; Kavzoglu and Mather, 1999).

CHAPTER THREE

The study area

3.1. The Jeffara Plain characteristics

The Jeffara Plain is located in the North-West of Libya and covers an area of about 26,000 km^2. It is near to the coastal zone of the Mediterranean Sea at a latitude of approximately 32°35'N. Rainfall in the region is approximately 100–200 mm per year (Pallas, 1980). In the last half of the 20^{th} century, the region has suffered from desertification; soils have been degraded, vegetation cover has disappeared and the level of groundwater has lowered with evidence of wells becoming dry (Ben-Mahmoud *et al.*, 2000).

Almost 95% of the population of Libya lives in the coastal region in the north, and the rest are widely scattered in oases in mid- and southern Libya. According to the estimated population distribution in Libya in 2001 (National Information Authority of Libya, 2002), people tend to concentrate in two centres (Figure 3.1): the first is in the northwest (Jeffara Plain) where about 60% of all Libyans live and which includes the city of Tripoli, the capital of Libya, where more than one million people live. The second centre is in northeastern Libya (Ben-Ghazi Plain). The main reasons for this concentration are the availability of fertile soils and seasonable, moderate climatic conditions.

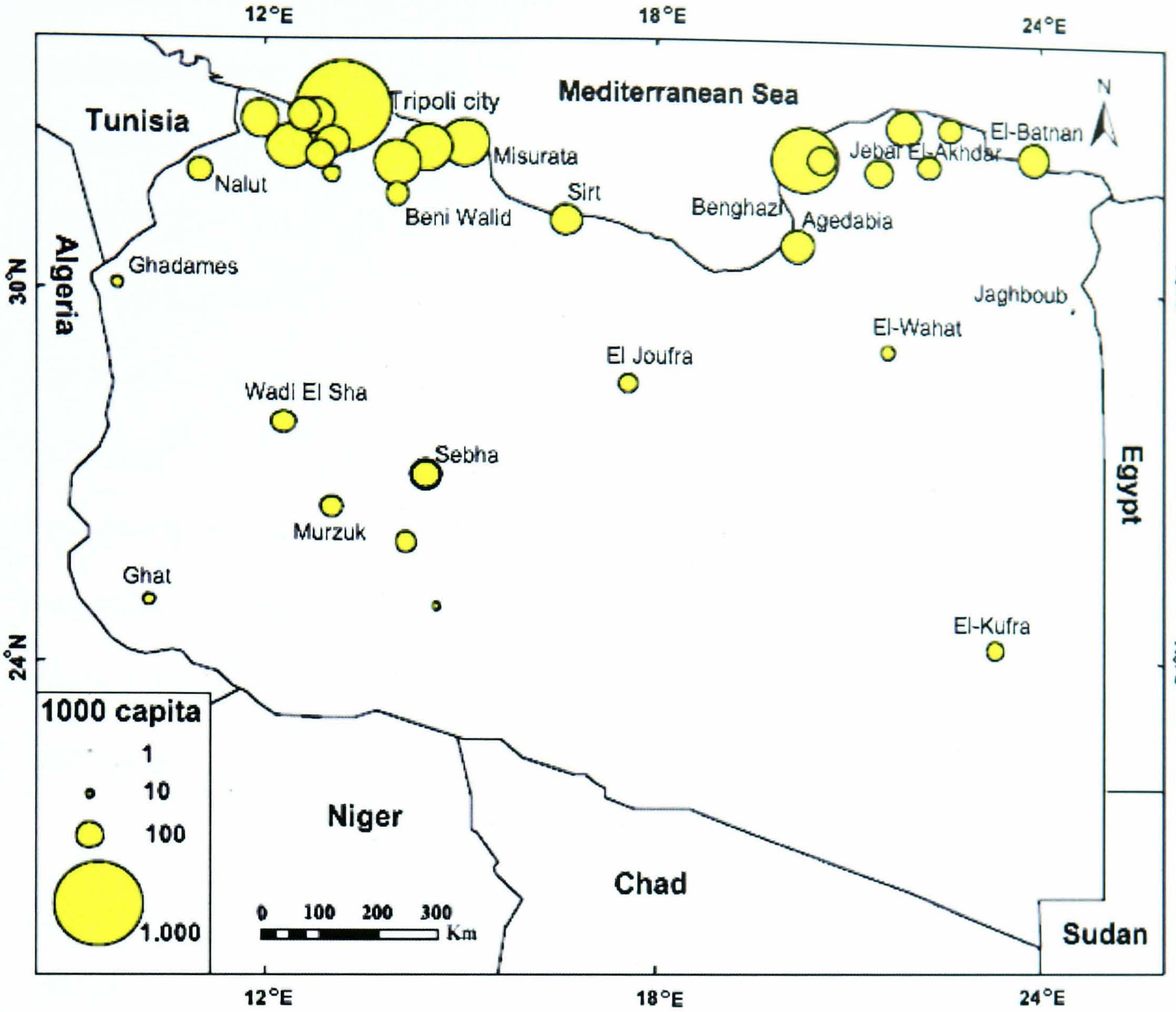

Figure 3.1. Spatial distribution of the population in Libya, 2001, (National Information Authority of Libya, 2002).

3.1.1. Jeffara Plain aquifers

The study site is located in the Jeffara Plain aquifer which is a part of the Western Jamahiriya System (WJS) (Figure 3.2). It is the principal aquifer used by the population in the area and is an unconfined upper aquifer, consisting of mainly Quaternary sandstones and riverine sediments underlain by Miocene sandstone with clay lenses located near the base (El Fleet and Baird, 2001). The aquifers that play an important role in groundwater flow and storage in the Jeffara Plain are as follows and again based upon the description by Pallas (1980):

(i) The Quaternary-Pliocene-Upper Miocene aquifer consists of sand, as calcarenites and clay. The saturated thickness of the aquifer varies from 10 to 150 m.

(ii) A thick series of sandstones forms another important aquifer which is located in the central and eastern part the plain. The age of the sandstones is attributed to the Lower Cretaceous-Upper Jurassic (Kiklah Formation). In some places, the sandstones probably belong to the Upper Triassic (Abu Shaybah Formation). The thickness of the aquifer complex ranges between 100 and 350 m.

(iii) Dolomitic limestones of the Azizia formation (Middle Triassic) are well developed in the south-central part of the Jeffara plain. In the western part of the plain, the Azizia Formation also seems to form a good aquifer (although with poor quality water) in the area where its depth does not exceed 300 to 400 m (Pallas, 1980). The deterioration in groundwater quality in the immediate vicinity of the coast in recent years is evidence that seawater intrusion is occurring along the northern coast (Krummenacher, 1982).

3.1.1.1. Hydraulic behavior of the aquifer

The groundwater flow in the region is divided to three parts (Pallas 1980). In the south-central part of the Jeffara Plain the groundwater flows mainly in the Triassic sandstones and dolomitic limestones. The flow is likely to originate a few kilometers south of the jabal escarpment. To the north, most of the groundwater flows into the Quaternary-Pliocene-Upper Miocene aquifers but part of the flow probably also recharges the lower Miocene and Mesozoic sandstones aquifers confined by the clays of the Middle Miocene

In the eastern part of the Jeffara Plain the groundwater flows mainly in the Mesozoic sandsatone (mostly Kiklah). This groundwater flow is in continuity with the general south-north flow in the eastern Suf Ajin basin. To the north, most of the groundwater flow remains in the Mesozoic sandstone (associated wuth the lower Miocene aquifer). The shallow aquifer (mostly Quaternary and Upper Miocene) becomes independent and has its own direct recharge. Deeper aquifers in the Triassic dolomites (Azizia) and sandstones (Kurrush) are likely to contain poor quality water.

3.1.2. Topography

The Jeffara Plain is mostly flat, although it can be divided into three different areas: the coastal area, the central area and the foot of Jebal Naffusah in the south (Western Mountains) mountain area with an altitude of between 450 and 1000 m.

3.1.3. Geology of Jeffara Plain

The Jeffara Plain is covered by Quaternary deposits with occasional outcrops of limestone hills belonging to the Azizia Formation. Calcarenites, covered by coastal sandstones and brown silts form the coastal strip. The central parts are covered mainly by poorly consolidated aeolian deposits mixed with brownish silts. The southern border of the central part interlocks with the foot of the mountain strip, which is made up of coarser fluvial sediments (Sadeg and Karahanolu, 2001).

3.1.4. Climate

The area has a Mediterranean climate with moderate temperatures and rain during the winter months which are exploited to some extent by grain farms (Pallas, 1980). The average temperatures are 30°C (86°F) in summer and 8°C (46°F) in winter; annual precipitation averages 100–200 mm and falls mainly in winter. A hot, very dry and sand-laden scorching wind called El Ghibli, which can raise the temperature up to 40°C, occasionally blows into the usually humid coastal towns (Kanter, 1967). The highest temperature ever recorded on Earth (57.8°C) was experienced in Libya on the 13th September 1922 (Martyn, 1992) at Al-Azizia city which is located in the Jeffara plain, about 10 km south of the study area.

3.1.5. Study area location

The study site selected is an area in the northern part of the Jeffara Plain (32°35'-32°55'N, 12°33'-13°21'E) located near the coastal zone (Figure 3.2a and b) and covering an area of about 1000 km^2. This area is an important part of Libya as a large number of people live between two of its most important cities; Tripoli with 30% of Libya's 5.6 million population, and El-Zawia city as the fourth biggest city in Libya and one of the most fertile agricultural areas in the country. The region contains large tracts of arable land, with many types of trees grown in the area, including orange trees, olive trees, palm trees and other fruit trees. All agricultural activities in the area depend on groundwater supply for irrigation as there is no other viable source of water.

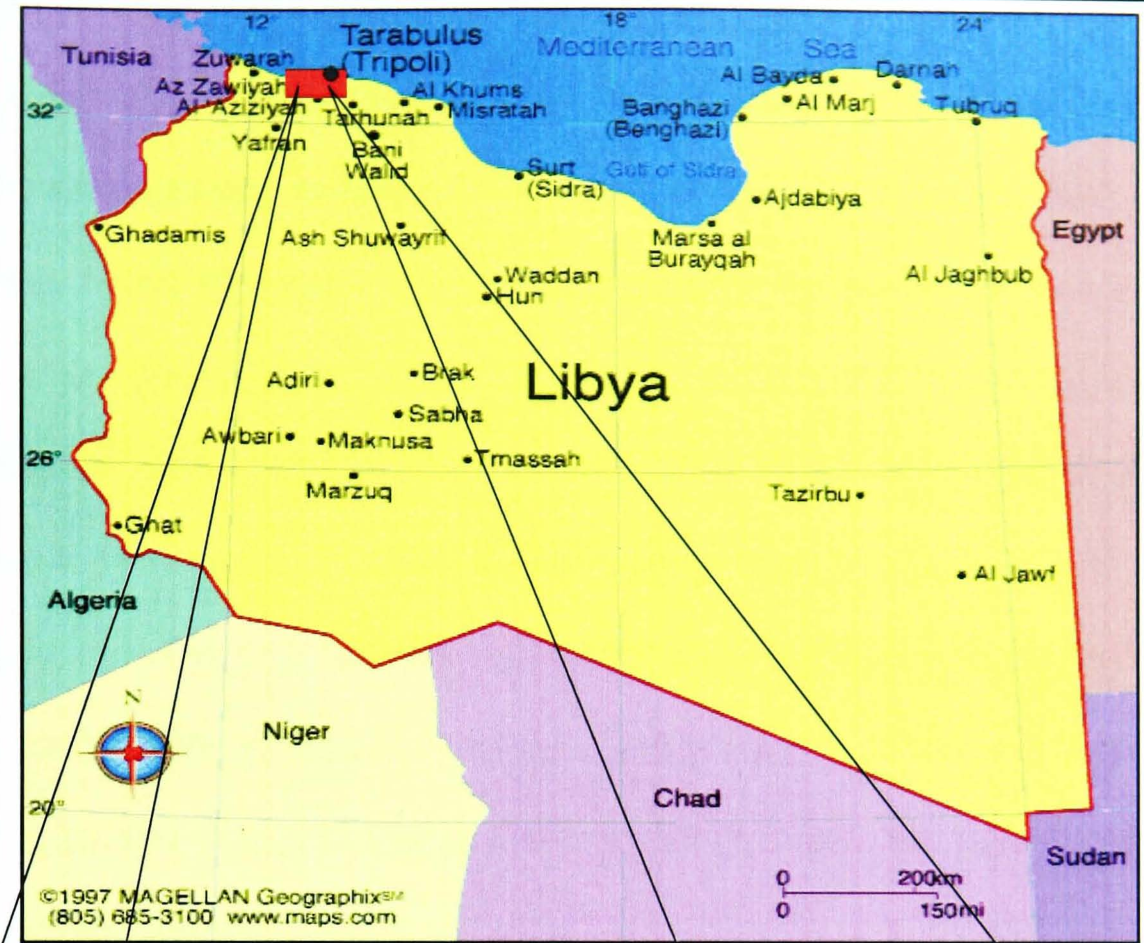

Figure 3.2a. ■ *Location of the study area in the Jeffara plain, NW Libya (source: infoplease, 10/10/2008).*

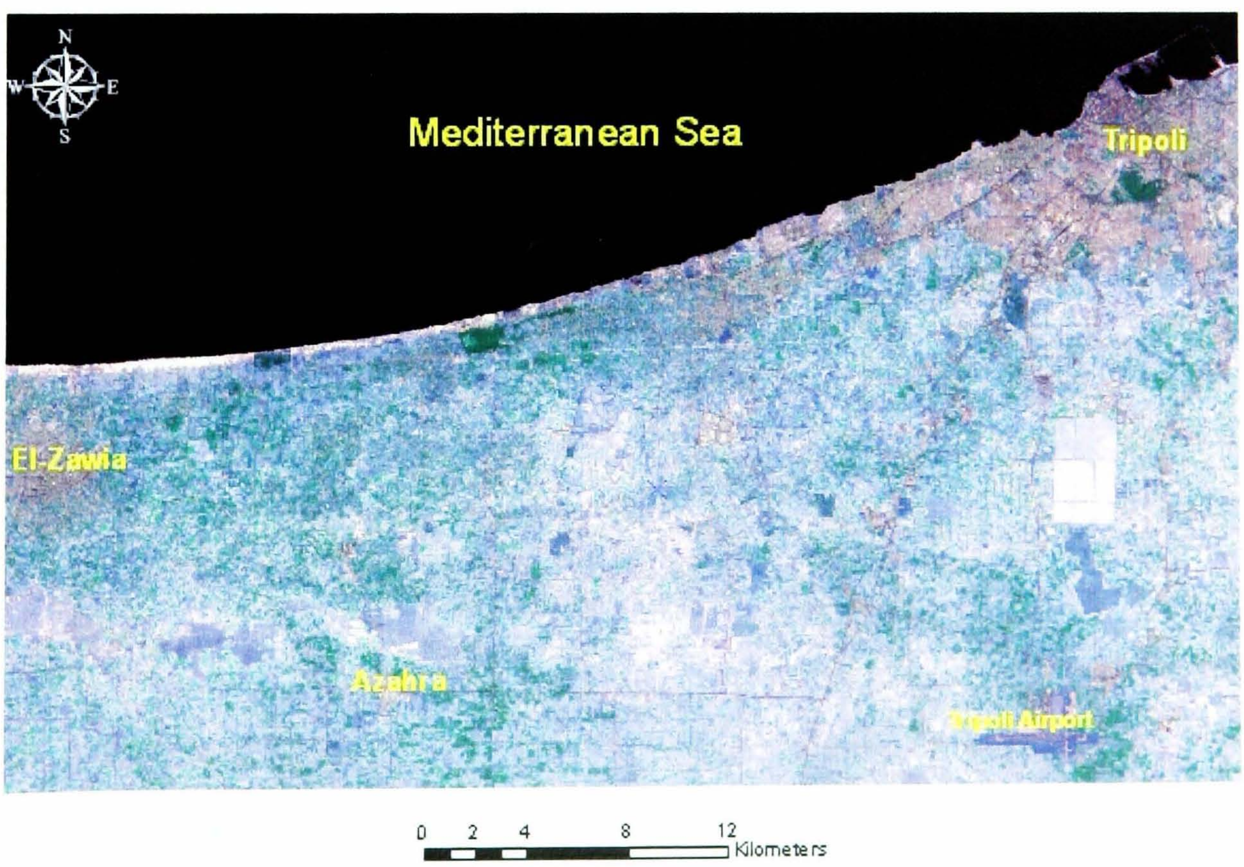

Figure 3.2b. The study area depicted in a Landsat TM-5 scene (2000).

3.1.6. Agricultural activities

Both Irrigated and non-irrigated agricultural projects are found within the area. Irrigated agriculture includes the growing of citrus trees and other trees, such as olives and dates, as well as annual crops such as cereals, alfalfa, melons, onions, and potatoes (Library of Congress, 1988). Non-irrigated agriculture includes the growing of wheat and barley, which occurs mainly in the south of the area. Many farmers have recently combined tree crops (grown mixed) such as olives, dates, grapes, almonds and citrus trees with cereal production growing plants in the spaces between trees. In addition, there are fields in the study area where citrus fruits tend to be grown on their own (i.e. not mixed with other trees). Table 3.1 lists the estimated yields for various crops in Libya including citrus fruits and illustrates that all crop yields in Libya are highly dependent upon irrigation for water.

Table 3.1. Estimated crop yields in Libya in 2000.

Crop	Yield in kg/ha	
	rainfed	irrigation
Wheat	650	1 400
Barley	450	750
Millet	1 200	-
Dates	2 800	8 600
Potatoes	-	7 300
Pulses	600	1 500
Citrus	-	10 500
Apples	8 300	20 000
Grapes	2 300	10 400
Vegetables	6 700	13 000
Olives	700	2 200
Groundnuts	-	1 800

Aquastat survey 2005 (FAO)

Table 3.2 shows the citrus production in Libya compared with other parts of the World. The production of citrus fruit in Libya decreased in the period from 1982 to 1984 and 1992 to 1994; also the percentage of the growth rates in Libya was negative during the same period. On the other hand, it is very clear that the total production of citrus fruit in

Libya decreased in the period from 1982 to 2005 compared with other countries, and comparing with Algeria as the same part of the world, the production has decreased from 1982 to 1994 the increased in the rest of the period which might related to other factors. A very limited data of the citrus production and no sufficient information available the questionnaire survey were used for farther analysis.

Table 3.2. Total citrus fruit production in various parts of the world: actual and projected.

TOTAL PRODUCTION					GROWTH RATES	
	1982--84	**1992--94**	**1995**	**2005**	**1982-84**	**1992-94**
	Average	Average	Projected		**1992-94**	**2005**
(thousands of tons)					(percent / year)	
World	54 322	74 651	78 173	95 783	3.23	2.10
Developing	29 343	47 328	50 064	63 645	4.90	2.50
Africa	3 742	4 804	4 931	5 677	2.53	1.40
North Africa	2 925	3 980	4 094	4 682	3.13	1.36
Algeria	283	263	275	315	-0.73	1.49
Egypt	1 358	2 230	2 472	2 744	5.08	1.74
Libya	**100**	**96**	**88**	**95**	**-0.39**	**-0.06**
Morocco	1 009	1 196	1 065	1 278	1.71	0.55
Tunisia	174	195	194	251	1.13	2.12

(Intergovernmental Group on Citrus Fruit, 1998).

It is clear that citrus production has declined, however the reasons for this decline are unclear and possibly dependent upon groundwater status given that these types of crops demand a significant input of water.

As shown above Table 3.2 worldwide production of citrus fruit increased globally during the period from 1982 to 2005 (Intergovernmental Group on Citrus Fruit, 1998). This increase is noted in most countries, but not all. Most countries show an increase in the average production rate; however in Libya, production has decreased (Table 3.2). This decrease in the production of citrus fruit is evidence that the total area under citrus fruit cultivation has reduced, which may be related to water availability, given that production in other North African countries has generally increased. In addition, Table 3.3 illustrates total citrus net trade as a global distribution which shows that there is a projected increase in the trade of citrus fruit. This increase in trade means that the price of citrus fruit is generally increasing (Intergovernmental Group on Citrus Fruit, 1998). Therefore, a collapse in price or other economic factors are unlikely to be a significant factor driving changes in the agricultural activities in Libya, and the Jeffara Plain in particular.

Table 3.3. Total citrus net trade from 1982 to 2005

	NET IMPORT FRESH				GROWTH RATES		NET EXPORT FRESH				GROWTH RATES	
	82-84	**92-94**	**1995**	**2005**	**82-84**	**92-94**	**82-84**	**92-94**	**1995**	**2005**	**82-84**	**92-94**
	average			Projected	**92-94**	**2005**	average			Projected	**92-94**	**2005**
	thousands of tons				Percent / year		thousands of tons				Percent / year	
World	6 401	6 854	6 690	9 822	0.69	3.04	7 307	8 161	8 721	9 820	1.11	1.55
Developing	638	671	719	1 541	0.51	7.18	2 111	2 223	2 354	4 124	0.52	5.29
Africa	6	6	6	43	0.84	17.55	814	754	716	1 049	-0.76	2.79

(Intergovernmental Group on Citrus Fruit, 1998).

3.2. Summary

The study area is part of one of the most economically important regions in Libya, as the population distribution indicates. There are many reasons for this importance, such as the availability of fertile soils and a seasonable, moderate climate. Several studies have noted, the region suffers from desertification and soil degradation (erosion) (Ben-Mahmoud *et al.*, 2000; Oune, 2006) and lowering of the groundwater level (hydrological data), but the Jeffara region is still an important area for agriculture. As the limited of the data which support of the citrus production, questionnaire survey and informal interview can be used to provide evidence of reduce of the citrus fruit production.

CHAPTER FOUR

Data acquisition and preparation

Several types of data covering the study area were used in the analysis, including ground data (e.g. groundwater data and field observations), satellite imagery and other ancillary data (e.g. questionnaire survey).

4.1. Piezometric well and groundwater data

Groundwater data were provided by the Libyan General Water Authority (LGWA), collected by measuring the groundwater level from a number of piezometric wells situated in the region (Figure 4.1) (Appendix I), as the availability of the boreholes data were used to show the dramatically fallen of the groundwater level in the region.

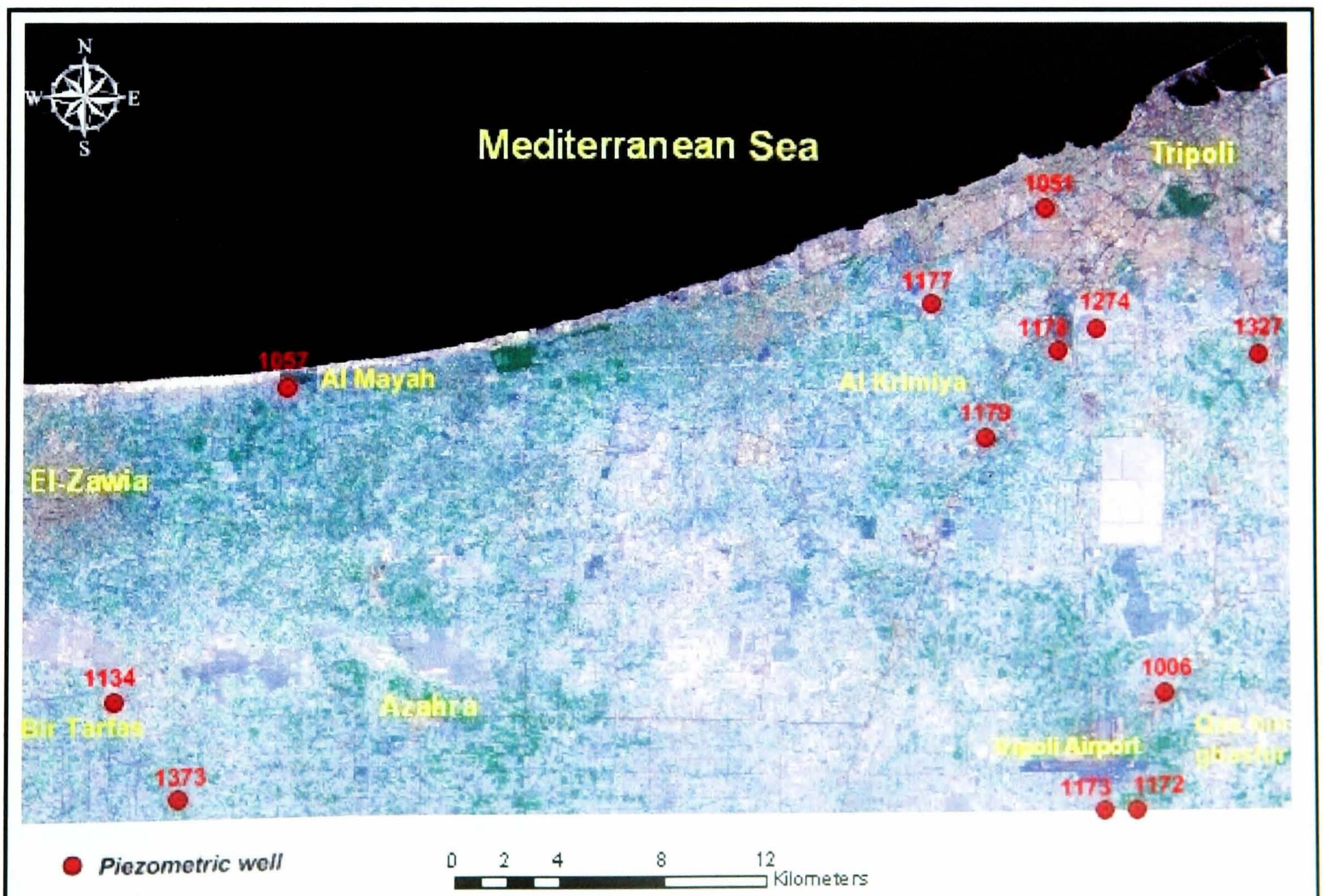

Figure 4.1. The location of the piezometric wells used to measure groundwater level in the study area (LGWA, 2005).

In the case of those sites which are not covered by piezometric wells such the centre of the study area, information on groundwater was collected from the many farms that have their own wells together with the data collected as part of the questionnaire survey.

4.2. Field visit and collection of ancillary data

The collection of training and validation data is important for most applications of remote sensing. One of the most significant aspects of such data is to identify the relationships between image data and conditions at corresponding points on the ground, in order to validate any analysis and processing (Campbell, 2006). In many cases the only way to acquire such data is by making a field visit where, for example, ground control points (GCPs) can be located and assessed independently on the ground (e.g. by GPS) to check the accuracy of the geometric correction of the imagery used, with the potential to reduce or quantify errors present (Clavet *et al.*, 1993; Kardoulas *et al.*, 996). Also, field observations can double-check features observed in the classified image, in addition to other available reference sources.

Fieldwork was carried out in 2006 to check both the geometric correction of the satellite images of the study area and the accuracy of the classification. It was also conducted to visually assess the condition of the modern vegetation cover. The fieldwork was conducted during the same season (between June and August) as the satellite images were acquired to ensure that the vegetation was in a similar condition for both datasets. Additionally, a questionnaire survey and some informal interviews were carried out with farmers who live within the study area, with the aim of collecting information relating to groundwater changes and agricultural activities, plus any perceived relationships between them.

4.2.1. Visit preparation

After completing the initial image classification of the Landsat TM-5 images with training areas derived from existing maps and local knowledge, preparations were made for the field visit. The study area was divided into five small areas of interest to provide more manageable areas within which to collect detailed data (Figure 4.2). The areas were selected to compare the changes in land cover at different sites within the study area (e.g. coastal sites vs inland sites), and also to exclude some other effects such as urban growth around the cities, where land cover change is likely to be less affected by groundwater conditions. In addition, the areas selected appeared to have displayed the greatest change in vegetation cover, especially for land cover types including citrus fruits which are the most common type of trees grown in the area, as well as other vegetation types, including olive trees, annual crops and semi-natural vegetation. Fourteen points were selected in each of the five areas, preferentially at locations that had shown significant changes in vegetation cover during the study period from 1988 to 2000. In addition, seven further points in each area were selected as reference points, as they showed little or no changes in land cover.

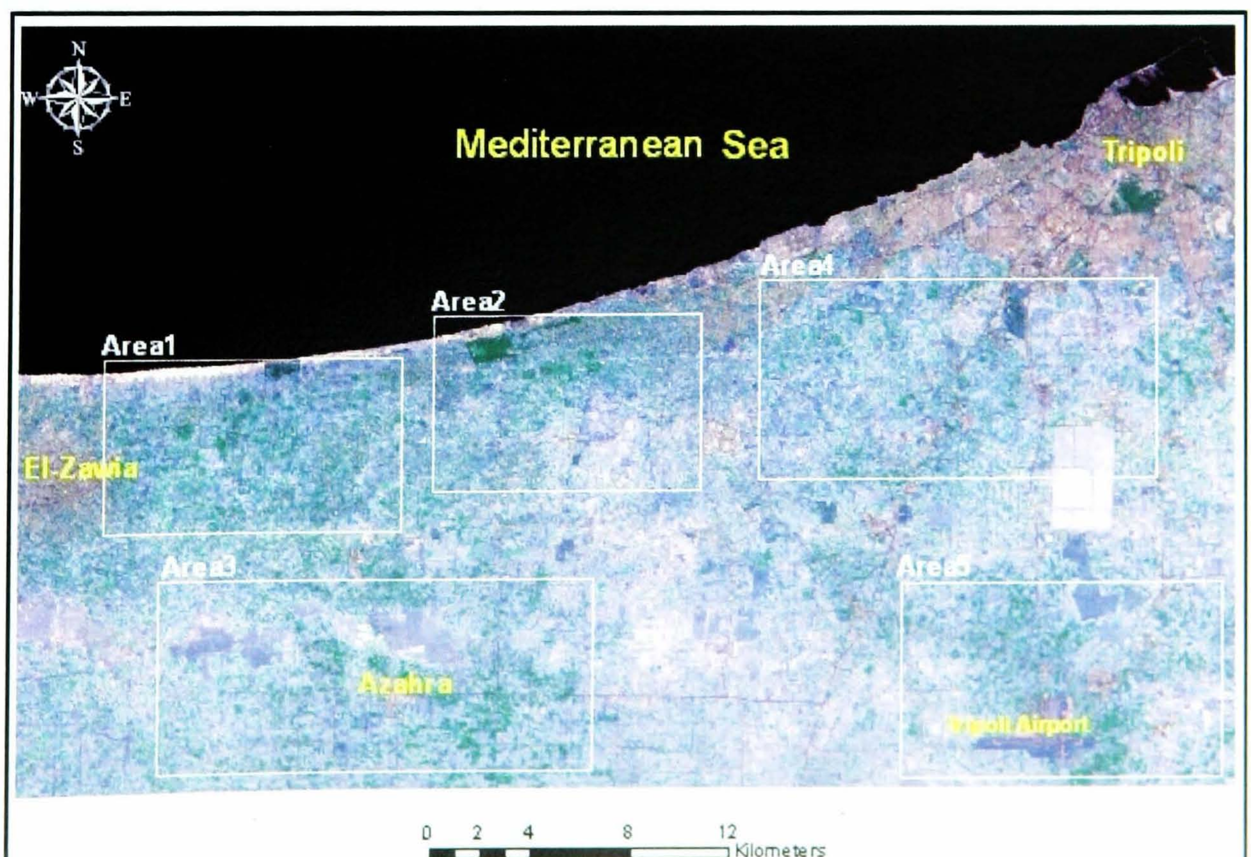

Figure 4.2. The five areas of interest in the study area.

The points selected for the field visits were well distributed across the areas of interest, but biased slightly towards points that were easy to access. A table for each area was prepared in advance of the visit that contained the latitude and longitude of the points determined from the image to compare with the co-ordinates observed in the field with a GPS (Appendix II-A). In addition, the table included columns to index photographs taken at each point, and a column for comments to describe the condition of land cover and any extra information as required.

4.2.2. Field data collection

Various data were collected in the field. Firstly, the co-ordinates of the points selected from the image were checked with a hand-held Garmin GPS 12XL. This device features 12 parallel channels for fast satellite acquisition with an accuracy of 15 m (Garmin 2008). This was considered sufficient given the 30 m spatial resolution of the Landsat TM data. These data were used to check the accuracy of the geometric correction of the images. The same points were subsequently used to validate the land cover classification. At each point, photographs were taken (e.g. Figure 4.3) to record the current state of the vegetation cover.

Figure 4.3. A farm in Area 1 containing orange trees: photo A is of an orange field which is affected by water availability; B, C and D are other field sites where some of the trees have died and have been cut, (6th July 2006).

4.3. Questionnaire survey

There is a paucity of information from both government statistics and the research literature that independently validate the changes in vegetation and agricultural activities observed in the region. While a land-use map of 1:50 000 scale (produced by SCET International in 1981) exists, there has not been another produced since. However, a recent project, conducted by the Food and Agriculture Organization of the United Nations (FAO), begun in 2000 and entitled "Mapping of Natural Resources for Agriculture Use and Planning in Libya" aims to rectify this situation but the results have not yet been published, and few details as to the resolution, detail and accuracy of any maps produced as part of this project are not available.

To rectify this lack of independent information on land cover change, and hence validate remote sensing estimates of any change, a questionnaire survey and series of informal interviews were undertaken in July 2006. These were designed to collect information from farmers directly relating to groundwater changes and agricultural activities across the region. Questionnaire surveys are particularly useful for eliciting people's attitudes and opinions about a subject (Malafferty, 2003). All information collected through the questionnaire survey was used to identify perceived links between groundwater changes and land cover change in the study area, evidence of changing vegetation cover patterns that may be identified by remotely sensed imagery.

The aim of this chapter is twofold. Firstly, it will describe the implementation and results of the questionnaire survey highlighting the main perceived drivers of change in agricultural activities and hence vegetation cover in the study area. It will then determine if there is a perceived relationship between change in groundwater levels and the changes in vegetation cover, through analysis of the opinions of the respondents.

4.3.1. Questionnaire survey design

The questionnaire survey is a method of data collection that ensures a high response rate within a short period of time (Malafferty, 2003). The technique of personal administration gives the researcher the opportunity to introduce the study subject and this usually motivates the individual to participate in the survey (Sekaran, 1992). It is a data compilation technique whereby each respondent is asked an identical set of specific written questions. The survey can be carried out by post or be completed in person, face-to-face. Alternatively, a respondent may be left alone to answer the questions, after which the form may be collected at a later time (Oppenheim, 1992). For this kind of data collection, the most useful questions are those that provide information of relevance to what the researcher is attempting to measure or elucidate. This may sound an obvious comment but careful design of the questions included in the survey is required.

In preparing survey questions one of the basic rules is to keep them simple and not use complex long words as these may confuse respondents. It is also important not to ask two questions in one, for example, "*Was the groundwater level in 2000 lower in comparison to the 1980s and of poorer quality?*" as this creates confusion as there is no clear response if only one characteristic is important (Malafferty, 2003). Another issue that has to be considered is that questions must be answerable, for instance, "*Do you approve or disapprove of people that go to football matches?*" indicated by two responses "*Yes*" and "*No*" which means that the answer categories are not appropriate to the form of the question. Answers such as approve and disapprove might be better (Oppenheim, 1992).

All questions in the questionnaire survey in this study were designed to be simple and understood clearly, and were designed, (i) to identify groundwater conditions (in terms of levels and quality), (ii) changes in vegetation cover, and (iii) to discover whether there is a perceived relationship between them. The questions served to provide data relating to the range of water table levels in locations not monitored by the LGWA, thereby providing a more densely populated network of sites as an independent reference source.

4.3.2. Questionnaire survey preparation

The questionnaire survey was prepared to collect information from farmers who reside in the region of the Jeffara Plain across the five sites of interest. A multiple response style was adopted and a total of 14 questions were formulated to collect the required information. As the study period was from 1988 to 2000 and the survey was in 2006, some questions were designed to determine groundwater conditions and vegetation cover in the period from the 1980s to 2000 and then compared with the following six years (2001 to 2006). In addition, an extra, open question was available for respondents to provide any other information which they considered pertinent to the study.

There were several different styles of questions used. For example, to identify a link between groundwater supply and the type of crops grown in the study area, a simple yes/no answer was required, for example:

Does a change in groundwater supply influence the type of crops and trees grown in this area?		
Yes	No	Don't know

Similar yes/no answers were requested in relation to questions relating to types of crops/trees grown in the area, for example:

Has the pattern and types of crops/trees grown in this area changed during the past 20 years?		
Yes	No	Don't know

Finally, some questions required a more specific categorical response, for example:

What was the depth of the ground water level in the year 2000?				
25-50 m	50-100 m	100-200 m	Over 200 m	Don't know

The possible categorical responses given to each question were determined from personal background knowledge, piezometric well data and the results of the initial land cover classification (Chapter 5). Finally, the questionnaire survey contained a small paragraph as a preface to explain its aim. To facilitate the process and to maximise the response rate, the questionnaire surveys were translated into Arabic, the local language. Both forms of the complete questionnaire in English and Arabic are presented in Appendix II-B.

4.3.3. Questionnaire survey response

Between 28th June and 10th August 2006, a sample of one hundred questionnaire surveys was supplied to a sample of farmers who resided in the study region, and own the farms and have their own well as interesting places as shown the change in the vegetation cover from the results of the initial classification for the satellite images. Those were selected to collect more information about the groundwater situation and the vegetation cover particularly in the farms of the orange trees. As well as to some individuals working for the Agricultural Ministry and Agricultural Research Centre in Tripoli, from their knowledge and experience about the groundwater and the agricultural activities in the region. The response rate was 85% (75% of the respondents from the farmers plus 10% from the ministers) and the results highlight many issues regarding groundwater level changes and vegetation cover. A complete set of responses is presented in appendix (II-B3).

4.4. Satellite sensor data

Four Landsat-5 TM images (1988, 1992, 1996 and 2000) of the study area (WRS, Path 189 Row 37) were supplied by the United States Geological Survey (USGS) at a single level of processing known as systematic correction (Level 4). The Landsat TM images have been chosen to discriminate areas of land cover change between the dates of acquisition particularly because they come from the same sensor thereby minimizing noise and uncertainty due to differences in sensor characteristics. They were acquired at a similar time of the year, so the effects of seasonal changes and different solar angles are reduced (Singh 1989, Zainal *et al.,* 1993). In addition, high spatial resolution data from SPOT XS, SPOT 5 and QuickBird sensors were used as validation data to help select training samples and were also used as reference data to assess the classification accuracy of the Landsat TM images. All satellite data used in this project were provided by the Biruni Remote Sensing Centre in Libya (BRSC) (Table 4.1).

Table 4.1. Properties of different satellite image data used during this research

Platform	Sensor	Spatial resolution	Path/Row	Date
Landsat-5	TM-5	30 m	189/37	25/08/1988
Landsat-5	TM-5	30 m	189/37	20/08/1992
Landsat-5	TM-5	30 m	189/37	15/08/1996
Landsat-5	TM-5	30 m	189/37	20/08/2000
Spot XS	HRV	20 m	72/284	23/06/1987
Spot 5	HRV	5 m	72/284	10/07/2002
QuickBird	BGIS-2000	2.44 m	N/A	22/06/2002

Whilst global land cover datasets are now freely available, such datasets were deemed unsuitable for this analysis. Land cover products derived from different instruments such as SPOT VEGETATION, MODIS, MERIS and NOAA AVHRR provide near daily multispectral imaging of the Earth's land surface with spatial resolution ranging from 250 to 1000 m. These land cover data usually have a narrowly defined set of classes (due to their global nature), plus the level of detail is unsuitable to identify change particularly in agricultural activities, where the intrinsic scale of vegetation cover is somewhat less than the spatial resolution offered by such products.

4.5. Image pre-processing

Using satellite imagery from different dates requires all images to be pre-processed in the same manner. This is to minimise potential errors and uncertainty in scale, geometry, and atmospheric conditions (Chavez, 1996; Foody *et al.*, 2003). Pre-processing steps are grouped into: (i) radiometric corrections, (ii) geometric corrections and (iii) image enhancement (Campbell, 2006).

(i) Differences in light attenuation and scattering due to the state of the atmosphere and solar intensity at different times may be significant sources of noise and errors. This problem can be addressed by radiometric calibration of the data (Chavez, 1989). Generally, the aim of radiometric correction is to remove, reduce and/or adjust any effects (e.g. sensor distortion, atmospheric effects, solar angle) which might influence the radiance received at the sensor (Chavez, 1996; Chen *et al.*, 2004; Coppin *et al.*, 2004; Roderick *et al.*, 1999; Song *et al.*, 2001). (ii) Geometric correction attempts to address the effects of image distortion due to image acquisition (i.e. sensor movement, topographic variation) and to convert the raw image coordinate system to a particular co-ordinate model projection. (iii) Image enhancement techniques include methods to enhance images, by histogram stretching and filtering, for example. These steps are used to alter the appearance of the data to potentially increase the information content visible in the image (Mather, 2004; Thomas *et al.*, 2004). Any pre-processing stage might include all techniques to prepare the data or just some of them, depending on the level of data acquired and the application it will be used for.

4.5.1. Radiometric correction

Passive satellite sensors record reflected and emitted radiation, with the amount of radiation received by a sensor affected by the atmosphere. Incident radiation and radiation reflected from the Earth's surface or features on the Earth will be scattered and absorbed by the atmosphere. The radiance measured at the satellite (L_S) is not the same as the amount of radiation that is reflected by Earth surface features (L_T) (Figure 4.4). Radiance (L_T) from paths 1, 3, and 5 contain intrinsic valuable spectral information about the target of interest. Scattering of incident radiation is the dominant effect of the atmosphere. Additional radiance from other paths, i.e. not the source - target – sensor path (path 1 in Figure 4.4) additive component of the received signal (L_P) from paths 2 and 4, includes diffuse sky, light and scattering from neighbouring areas on the ground, i.e. a proportion of radiation is received by the sensor that has been scattered from the atmospheric and does not relate to radiation reflected from the target object (Jensen, 2007). Therefore the total radiance received and recorded by the sensor becomes:

$$L_S = L_T + L_P \qquad (\mathrm{W\ m^{-2}\ sr^{-1}\ \mu m^{-1}}) \qquad [2]$$

Where:

L_S = Apparent at-satellite radiance.

L_T = Apparent radiance reflected by Earth surface feature.

L_P = Radiance from different paths as an additive component received at-satellite.

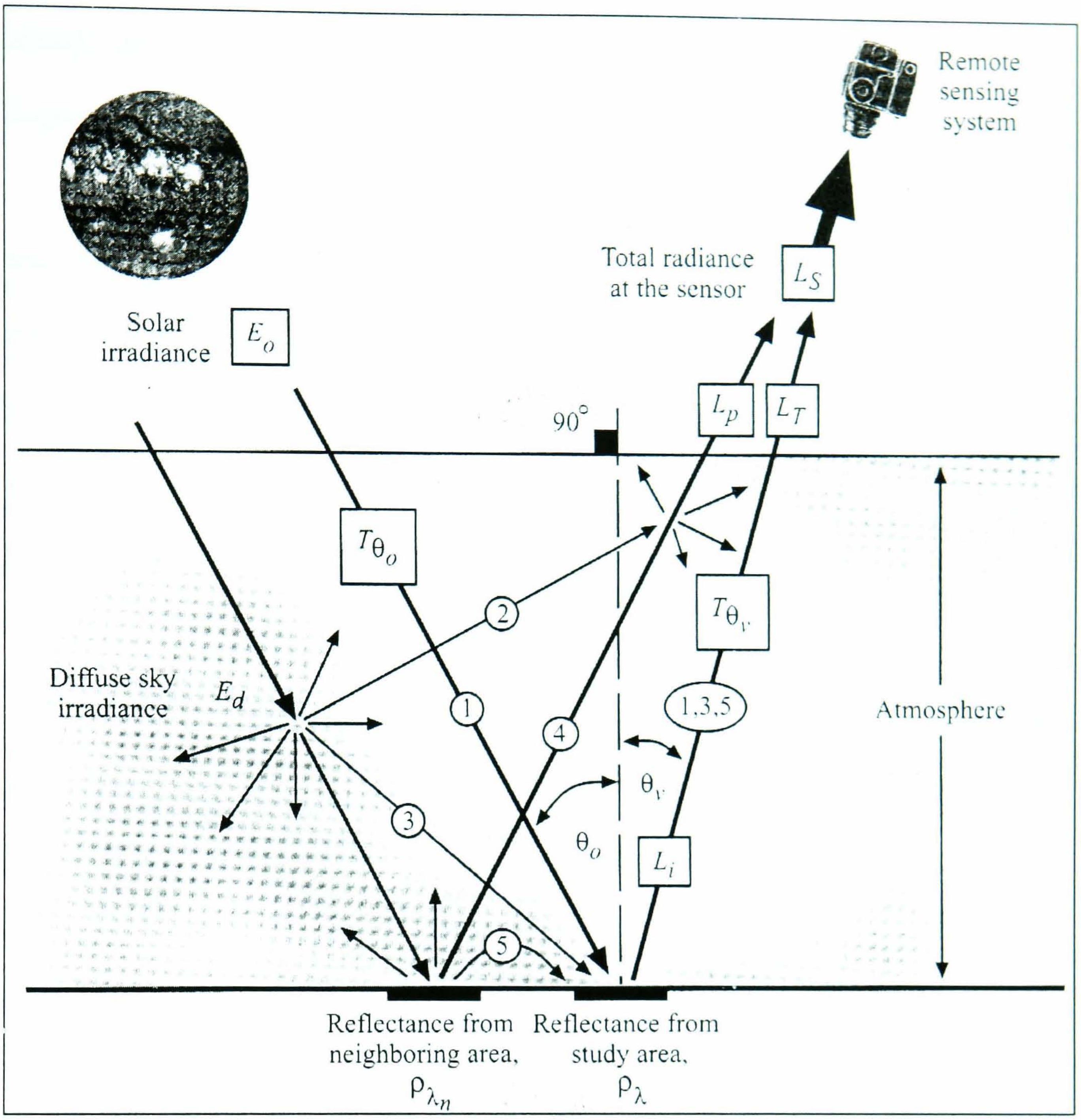

Figure 4.4. Component of the signal received by a satellite mounted sensor (Jensen, 2007)

Mather (2004) and Mausel *et al.* (2002) state that analysis and results using uncorrected remotely sensed data assume that the radiance of the features on the Earth have sufficiently different reflectance characteristics for differentiation and that atmospheric effects are not sufficiently great to effect their basic spectral separation. However, whilst this may be a reasonable assumption when using a single image, there are many reasons why such differentiation is not straightforward in multi-temporal data and thus supports the radiometric and atmospheric correction of remotely sensed data. For example, variable illumination and changing atmospheric conditions require such correction to identify land cover changes using multitemporal data (Song *et al.*, 2001), otherwise any change detected may not be attributable to actual change, rather than changing environmental conditions.

There are four potential steps in the radiometric correction process. The first eliminates sensor distortions by applying predetermined calibration coefficients. This ensures compatibility between wavebands, for example, as well as other sensor included noise. Secondly, atmospheric correction attempts to account for the additive effects of scattering by gas particles in the atmosphere, and the multiplicative effects of absorption. Topographic normalisation tries to account for anisotropic scattering of radiation from sloping surfaces, while the final step is the retrieval of reflectance (%). Only some of these steps are routinely applied due to issues of data availability and the reliability of the correction processes (Chavez, 1996; Ekstrand, 1996).

A plethora of methods is available for the radiometric correction of satellite image data ranging from simple to complex. Some of the most accurate methods are physically-based models, which require meteorological data collected coincident with remote sensing data acquisition (Mausel *et al.*, 2002). However, there are other methods, such as a regression-based correction (Levien *et al.*, 1998) and dark object subtraction (DOS) which are relatively simple to apply, require no meteorological information and are commonly applied for classification and change detection applications (Huguenin *et al.*, 1997), especially using Landsat TM data (e.g. Chen *et al.*, 2005; Song *et al.*, 2001; Foody *et al.*, 2003).

Two steps were followed here to apply the radiometric correction. The first was the calculation of apparent at satellite radiance. The second step was atmospheric correction to remove the additive effects of scattering and multiplicative effects of absorption.

4.5.1.1. Dark Object Subtraction (DOS)

DOS is the simplest, most widely used image-based model to atmospherically correct remotely sensed data (Spanner *et al.*, 1990; Ekstrand, 1996). The model basically assumes that any radiance received at the sensor for a dark object pixel is due to atmospheric path radiance (Chavez, 1996), i.e. the signal (received within the instrument IFOV) has been added to by radiation scattered within the atmosphere, rather than from the target itself which is dark or not illuminated and hence reflects no radiation.

Consequently, the value of pixels with the lowest DNs (i.e. from dark objects) are selected and then subtracted from the DN values across the whole image (waveband by waveband) to reduce scattering influences (Chavez, 1989). However, when using this technique the dark object needs to be selected carefully to ensure that the pixels selected contain the lowest DN values in the image. Conventionally dark objects selected are deep water bodies or dark vegetation under shadows (Chavez, 1996; Song *et al.*, 2001). As development to the original DOS model, Chavez (1996) proposed the COST model, including a correction for the multiplicative effects of atmospheric absorption. The cosine of the solar zenith (COS Z) is used as a surrogate for atmospheric path length, effectively accounting for the depth of the atmosphere, and hence the amount of atmospheric absorption. Using the cosine of the solar zenith improved the DOS results compared with results from *in-situ* atmospheric measurements (Chavez, 1996).

The COST model was used to remove the additive scattering component caused by path radiance based on the assumption that an absolute dark object existed within the image (Chavez, 1988, 1989; Fraser *et al.* 1992; Moran *et al.* 1992). A key assumption of this method is that the radiance received at the satellite is from some pixels in the image which are in complete shadow. A modification to earlier models includes a minimum reflectance from features on the Earth's surface which are in shadow (assumed to have a reflectance of 1% rather than zero), to account for diffuse illumination, for example from diffuse skylight (Chavez, 1996).

In implementing the COST model, several considerations justified its use in this case. Firstly, clear deep water (sea) formed a significant part of the image which made it easy to select dark pixels. Secondly, other data (e.g. simultaneous atmospheric measurement, such as water vapour, aerosols) which are required to apply other physically-based methods were not available (Chavez, 1996; Du *et al.*, 2002; Spanner *et al.*, 1990).

4.5.1.2. Radiometric and atmospheric correction steps

The radiometric and atmospheric correction was completed by following a sequence of steps. The first step was to convert the remotely sensed DN values to at-satellite radiance (W m^{-2} sr^{-1} μm^{-1}). Calibration coefficients were obtained from the header of the images (Appendix III) and the National Landsat Archive Production System (NLAPS). These included gains/biases and the solar elevation angle (Table 4.2).

Table 4.2. Calibration coefficients obtained from the header file of each image.

Date	Gains	Biases	Solar elevation
25/08/1988	+0.6024	-1.5	54°
20/08/1992	+0.6024	-1.5	54°
15/08/1996	+0.6024	-1.5	53°
20/08/2000	+0.6024	-1.5	55°

To calibrate each DN value to apparent at-satellite radiance (L_{SAT}) (W m^{-2} sr^{-1} μm^{1}) the following equation was applied:

$$L_{SAT} = G_{rescale} \times Q_{cal} + B_{rescale} \qquad [3]$$

where:

L_{SAT} = Apparent at-satellite radiance (W m^{-2} sr^{-1} μm^{-1})

$G_{rescale}$ = [Units of (W m^{-2} sr^{-1} μm^{-1}) /DN] (Gain coefficient from the header file)

$B_{rescale}$ = [Units of (W m^{-2} sr^{-1} μm^{-1})] (Bias coefficient from the header file)

Q_{cal} = Quantized calibrated pixel value in DNs.

The DOS technique was applied using the radiance measured from dark pixels (L_{HAZE}) obtained from pixels in deep sea areas of the image (Ahern *et al.,* 1977; Gordon 1978). The actual value subtracted was 99% of the DN value of dark water (i.e. leaving an assumed 1% reflectance from the dark object). Apparent radiance from a sloping terrain surface (L_T) was retrieved for each selected waveband by applying Equation 4.

$$L_T = (L_{SAT} - L_{HAZE}) / Cos(z) \qquad [4]$$

where:

L_T = Apparent radiance from a sloping terrain W m^{-2} sr^{-1} μm^{-1}

L_{SAT} = Apparent at-satellite radiance in W m^{-2} sr^{-1} μm^{-1} from Equation (1)

L_{HAZE} = Path radiance, i.e. DN of dark pixel

Cos (z) = Cosine of the solar zenith angle (angle of Sun from the vertical).

Further radiometric correction was not required as it was assumed that the anisotropic reflectance effects of topography were minimal due to the relatively flat terrain of the area.

4.6. Geometric correction

Raster digital images are often supplied in a "raw" file format which means that they are not referenced to any particular map projection system. They cannot be used directly as a map because they usually contain geometric distortions (of both location and scale) (Mather, 2004). The causes of these distortions range from variations in the satellite's altitude and attitude, as well as distortions such as Earth curvature (Figure 4.5), Earth rotation (Figure 4.6), topography, scan rate and panoramic effects. (Jensen, 2005; Thomas *et al.*, 2004).

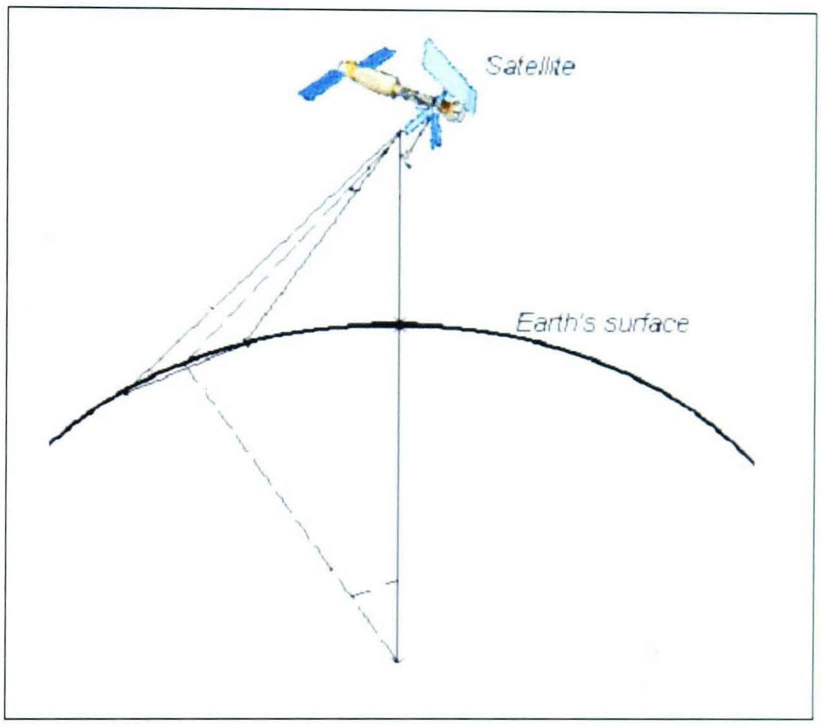

Figure 4.5. Earth curvature as a source of geometric distortion (Pohl, 1996).

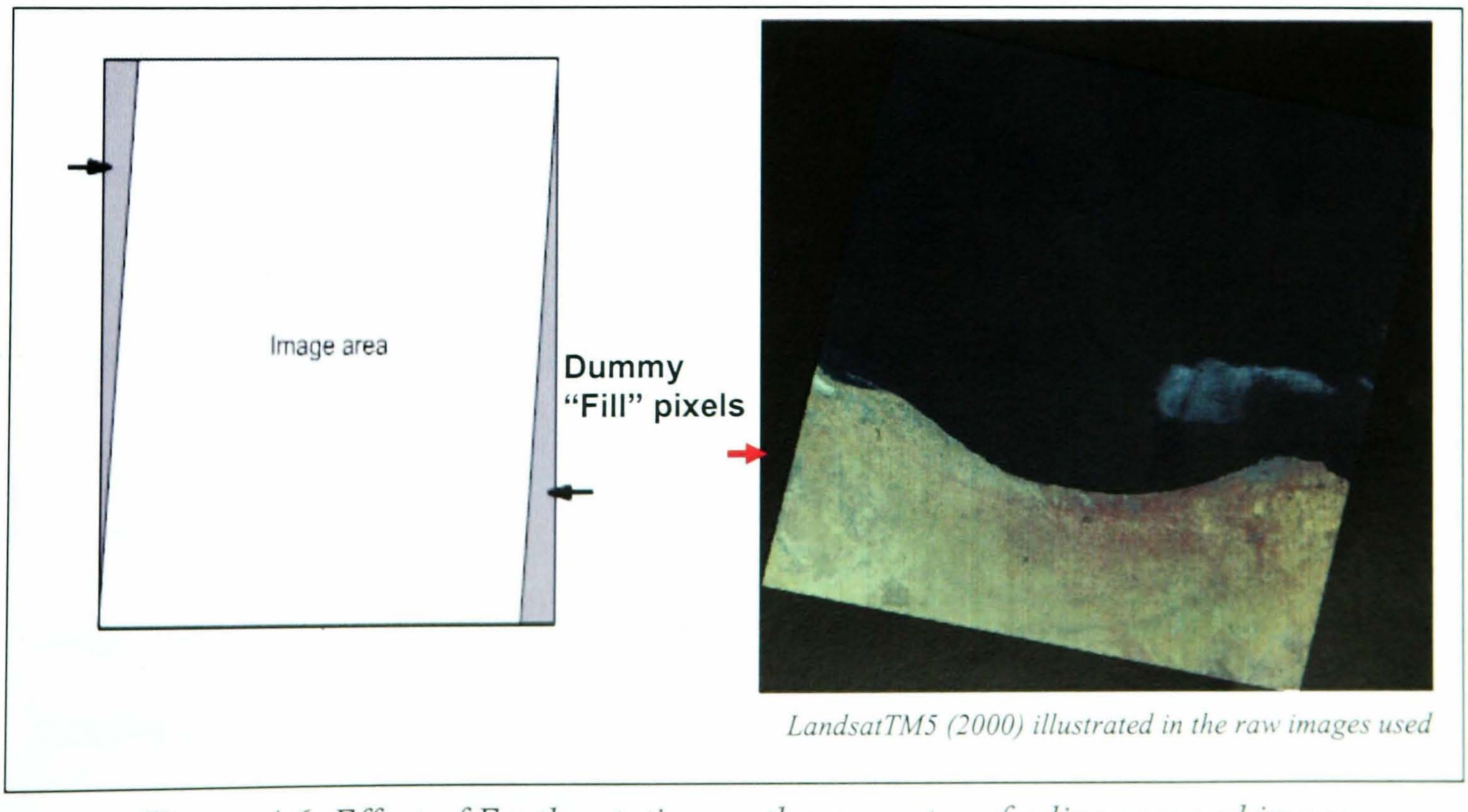

Figure 4.6. Effect of Earth rotation on the geometry of a line scanned image.

To extract information reliably from multi-source/multi-date remotely sensed images, the data must be corrected for these distortions and registered to a common co-ordinate system (Mather, 2004). The geometric correction process of satellite images involves modelling the relationship between the image and ground co-ordinate systems.

There are three commonly applied steps to remove the geometric distortions of satellite images. Firstly, the application of Orbital Geometry Models, which are dependent on information such as the type of the orbit of the satellite platform and corrected using data from the platform ephemeris. Secondly, a transformation to a new co-ordinate system based upon the use of ground control points (GCPs) is required. These are features of known ground location that can be accurately located on the digital imagery. They are usually acquired from a reference map, other images already georeferenced or by using Global Positioning System (GPS) and ground survey. The third step is to resample the pixel values to fill the output matrix transformed from the original image matrix in step two (Mather, 2004).

Different geometric models exist to transform the raster image to map co-ordinates. Several issues need to be considered when choosing a geometric model, such as the number of ground control points and the distribution of these across the image to ensure the whole image is rectified. There is also a relationship between the number of GCPs and the polynomial expression order; since each polynomial order needs a particular minimum number of GCPs (Mather, 2004). In selecting a polynomial expression, "A first-order polynomial is normally suitable for a transformation between two near rectilinear map systems. Raw satellite imagery can usually be transformed into a projection, such as UTM or State Plane, using first-order polynomials" (ERDAS Imaging HELP, May 2007).

The most common resampling methods used to assign the appropriate DN to an output pixel are nearest neighbour, bilinear interpolation, and cubic convolution. The nearest neighbour algorithm simply assigns to each location in the output matrix the pixel value of its nearest neighbour from the original system. It is a fast resampling technique and is appropriate for thematic data because it does not use an interpolation algorithm to calculate the pixel value in the production image but is simply copied from the raw image. Bilinear interpolation and cubic convolution techniques combine a greater number of nearby cells to compute the value of the transformed cell. The latter techniques use a biased averaging method and are only appropriate for continuous data, such as elevation or slope information (Mather, 2004; Thomas *et al.*, 2004) or when the radiometric integrity of the data is not a factor (e.g. in cartographic output / display).

In this project, the study area covers a small and relatively flat area. An image to map transformation method was used to georeference the Landsat TM5 satellite image from 1988. A mosaic of 12 1:50 000 topographic digital maps (UTM, zone 33 projection, WGS84 Datum) was prepared as a reference source. Given that a first order polynomial is sufficient for medium spatial resolution images of flat areas (Mather, 2004), this was selected as the most appropriate geometric correction model in this case. Ground control points (GPCs) were selected from both the image and map, which were spread across the land area within the image. Image to image registration was then applied by using the corrected Landsat TM5 1988 image as a reference image, to which all other images were referenced. Twenty GCPs were selected in each Landsat TM5 image (1992, 1996 and 2000), using clear image features such as roads or cross-sections as control points. A first order polynomial model was then used to reference each image to the original 1988 image.

The overall root mean square (RMS) errors for each correction was less than one pixel, although do not match exactly the 0.2 pixel that Towshend *et al.* (1992) suggest is required for 90% accuracy. However, the accuracy was demand appropriate on this occasion. Then the nearest neighbour technique was used to resample all images as it does not alter the radiometrically corrected pixel values (Table 4.3).

Table 4.3. The root mean square error (RMS) for the geometric correction of each image.

Data	Reference data	Number of (GCPs)	RMS (m)
TM 5 1988	Mosaic of Topo maps	20	0.6338
TM 5 1992	Rectified TM5 1988	20	0.295
TM 5 1996	Rectified TM5 1988	20	0.343
TM 5 2000	Rectified TM5 1988	20	0.317

In addition, the geometric correction of the images was checked using data collected in the field by selecting reference points from the images locating in the same points of the field visit using hand-held GPS (see 4.2.2). Appendix II-A2 illustrates the check points were used to calculate the RMS. The overall root mean square (RMS) was 50 m Easting and 54 m Northing. Whilst this is in excess of one Landsat TM pixel (30) it does include the positional uncertainty in the GPS unit. It is also represents the error associated with an image that has been registered to a much earlier image (1988) to relatively a crude topographic maps. In considering these factors, and the RMS values in table 4.3 it was described that this was programmatically appropriate level of correction.

4.7. Summary

The advantages of using images from the same sensor for mapping land cover change (Singh, 1989; Zainal *et al.*, 1993) were exploited here by selecting four Landsat TM images of the Jeffara Plain. Methods of pre-processing remotely sensed imagery are designed to compensate for issues including atmospheric effects and geometric distortions (Mather, 2004). The level of pre-processing required is dependent on the application and the level of satellite data used and also the problem to which the processed images are to be applied. In this case, the images were radiometrically/atmospherically corrected using the DOS/COST models (Chavez, 1996) and geometrically corrected to within one pixel using a first order polynomial model. Topographic normalisation was not applied as the area is relatively flat.

CHAPTER FIVE

Groundwater and vegetation change

5.1. Introduction

Groundwater is the main source of both drinking and agricultural irrigation water in Libya. It is widely believed that a dramatic lowering of the water table has led to changes in agricultural activities during the last twenty years in the region and this has resulted in changes in the vegetation cover. This is especially the case for citrus fruits such as orange trees, which are the most common kind of trees grown in the Jeffara Plain study area (Library of Congress, 1988).

5.2. Questionnaire survey results and analysis

The goal of the questionnaire survey was to acquire information about the area relating to the groundwater and change in agricultural/vegetation cover. The responses can be analysed by group according to, (i) the quantity of groundwater, (ii) the quality of groundwater, and (iii) the nature of vegetation change.

5.2.1. Groundwater quantity

The first part of the questionnaire survey was to ask whether groundwater was the main source of water used for irrigation in the region. In reply, 87% of respondents said that it was the main source, with 13% answering that it was not. The latter tended to be farmers who depended on rain-fed supplies to irrigate their crops and/or trees. Most of those farmers are located in Area 3 and Area 5 (both inland areas) where they are growing cereal crops such as wheat and barley and require much less water than other agricultural activities, such as citrus crops production.

Subsequently, questions were asked to identify the changes in the quantity of groundwater available during the past 20 years with specific reference to the perceived levels in the 1980s and changes, if any, over the last six years. With respect to both periods, the possible answers were as follows:

Shortage of supply	Intermittent	Sufficient	Not an issue	Don't know

In trying to draw a qualitative comparison between the two periods, another question with four response options asked respondents to state whether they believed there had been a change in the level of groundwater over the past 20 years in comparison with the previous period. The possible answers were as follows:

Less water	Similar	More water	Don't know

Both sets of responses suggest that groundwater availability has deteriorated over the study period, with 72% of respondents reporting that levels were 'sufficient' in the 1980s, while 55% reported a 'shortage' in recent times (Figure 5.1).

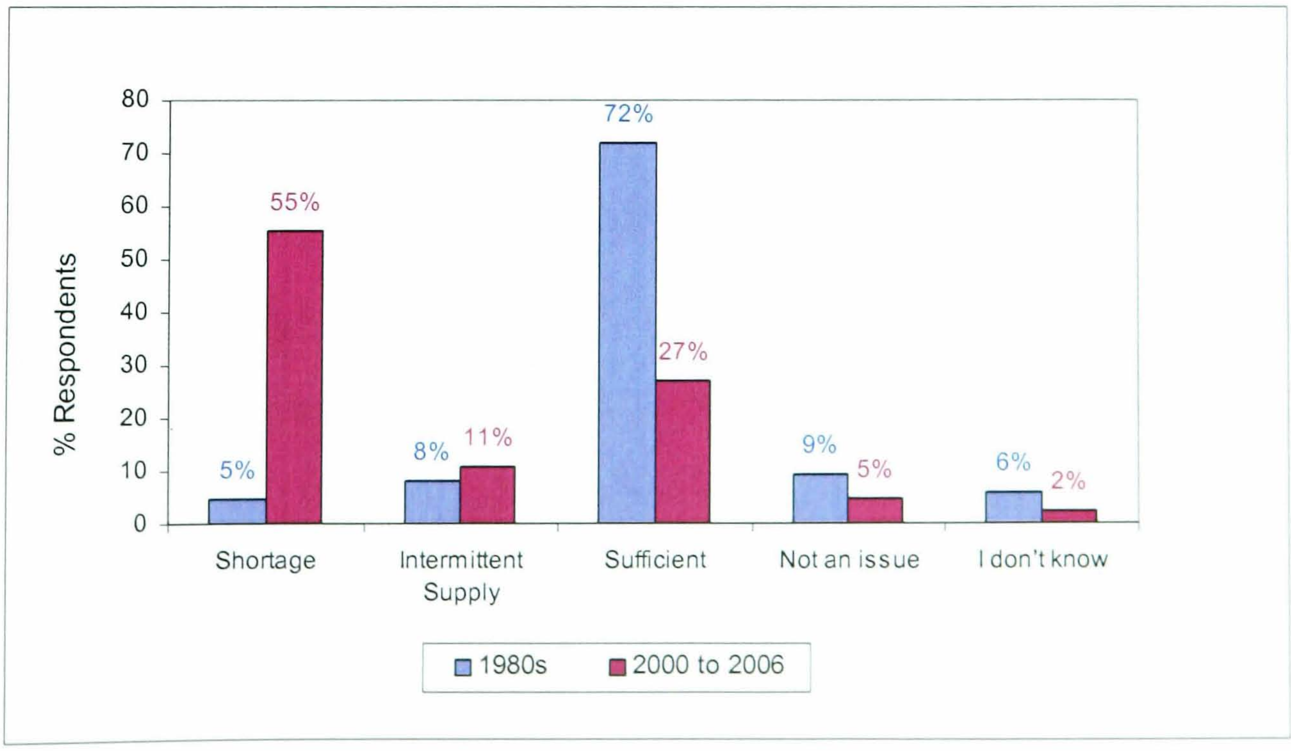

Figure 5.1. Perception of groundwater quantity in the 1980s compared with 2000 -2006.

Also, 86% took the view that levels of available groundwater have fallen since the 1980s, with just 12% of responses judging the availability of groundwater at similar levels (Figure 5.2). Most of those respondents were located in the coastal areas (1, 2 and 4) and as shown in Figures 5.4-5.6 the groundwater depth in the study area for 1980s, 2000 and 2006.

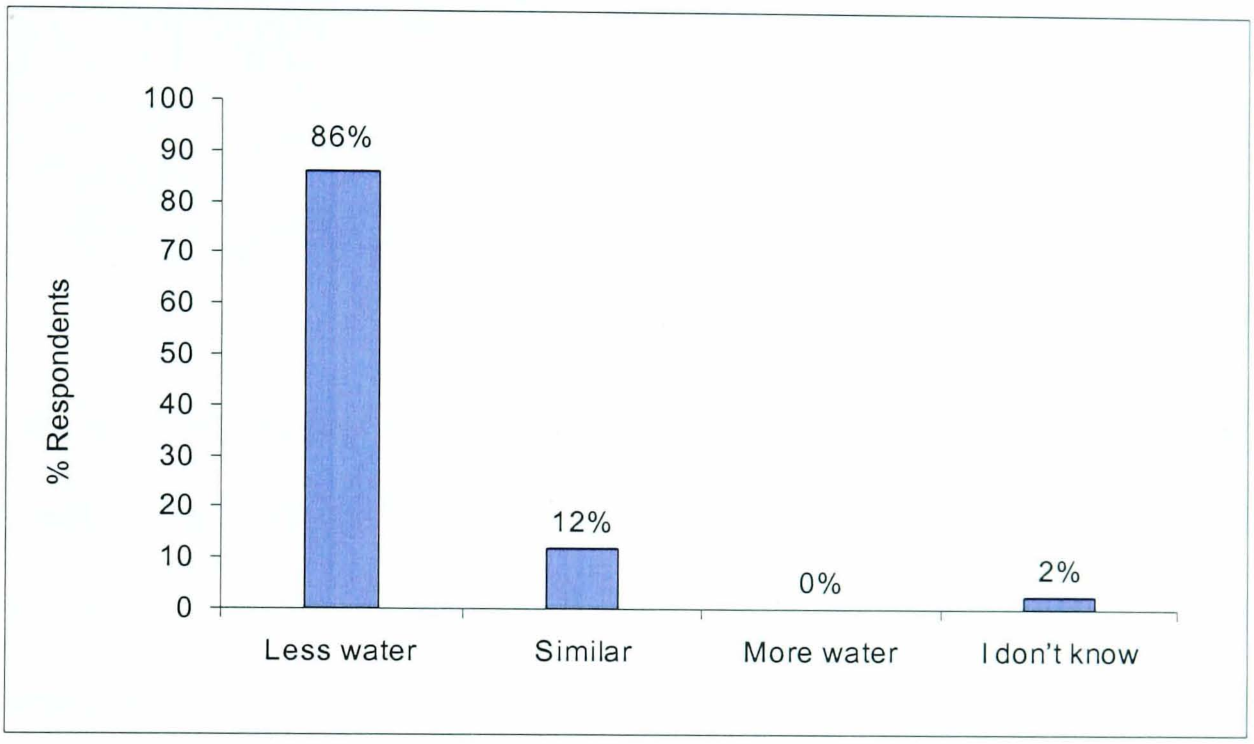

Figure 5.2. Comparison of perceived groundwater quantity in the 1980s and 2000-2006.

Three questions were then asked to identify the estimated level (i.e. actual depth) of groundwater across the study area. The first was related to the estimated depth of the water table in the 1980s, the second referred to groundwater levels in 2000 and the third to the conditions in 2006. Figure 5.3 shows clearly the change in the perceived groundwater levels over the past 20 years with a generally worsening trend and Figure 5.4, 5.5 and 5.6 illustrates the distribution of the questionnaire survey responses which provide the groundwater depth in 1980s, 2000 and 2006. The results illustrate that 38% of respondents put the level of groundwater at 25-50 m in the 1980s, while only 7% of respondents believed that the level was over 200 m in the same period. However, by 2006 51% of respondents put the level of groundwater at over 200 m deep.

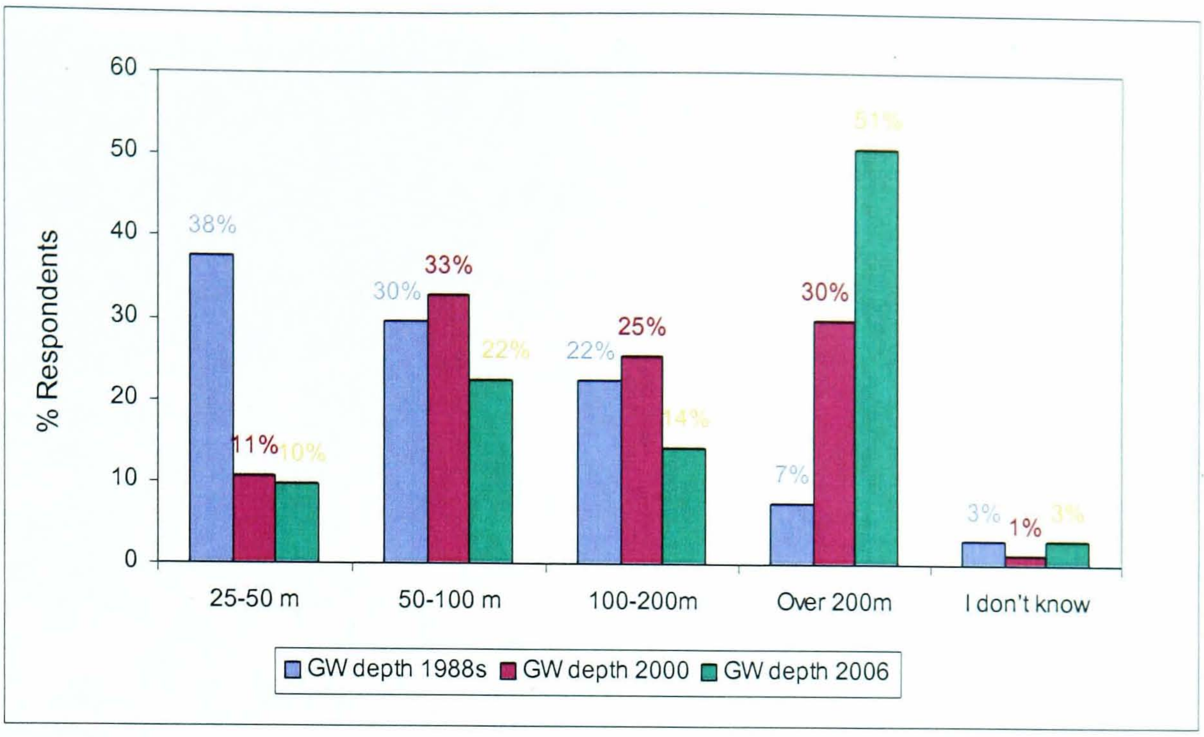

Figure 5.3. Estimated groundwater depth in different years during the period of study.

This change in perceived groundwater level appears more often over inland areas rather than coastal areas (Area 3 and Area 5). Referred to the responses of question nine in the questionnaires survey and the information from the informal interviews with the farmer, the clearly lowering of the groundwater level is related to the intensive use with almost no recharge, particularly in the inland area more than the coastal area.

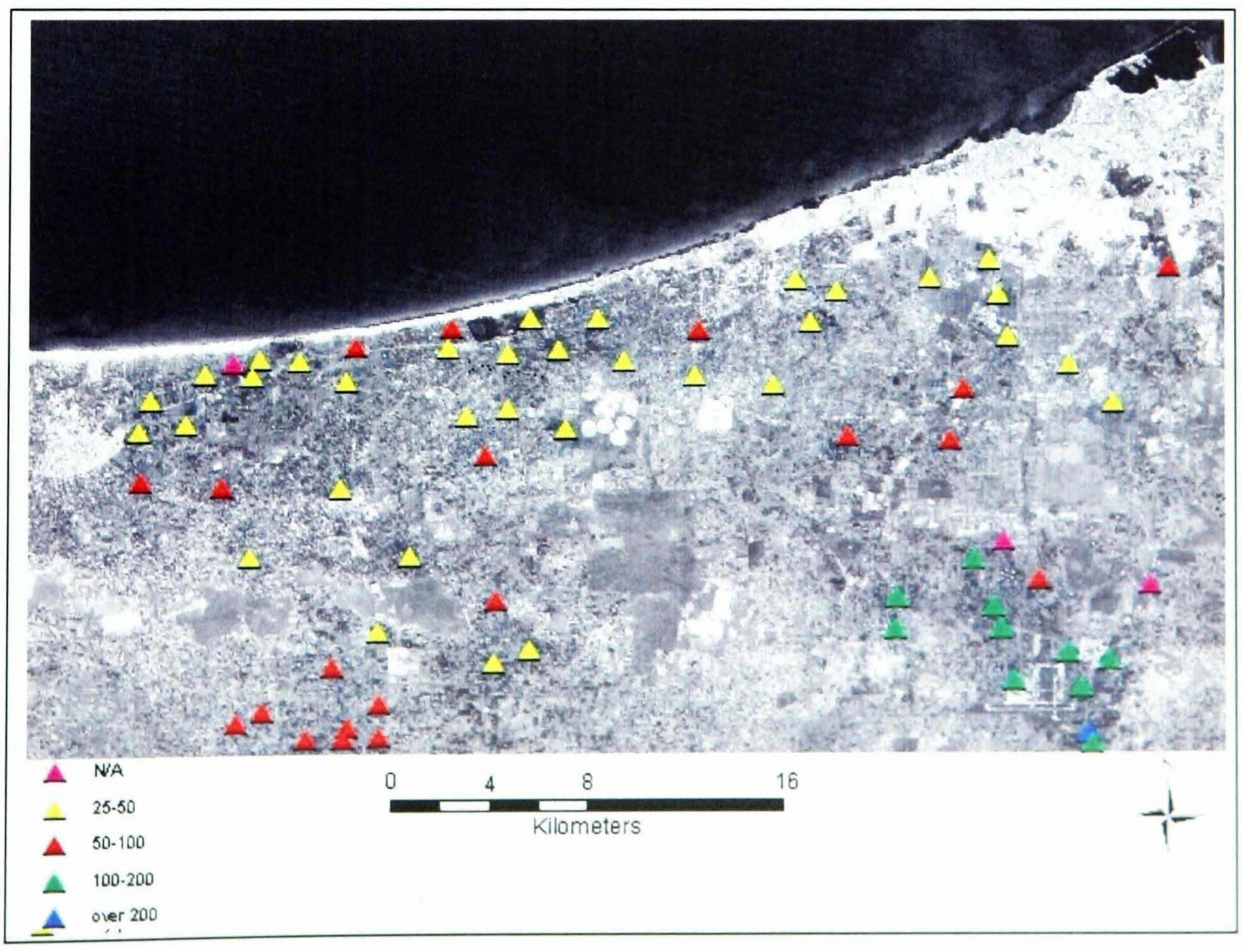

Figure 5.4. Spatial distribution of questionnaire survey responses (groundwater depth in 1980s).

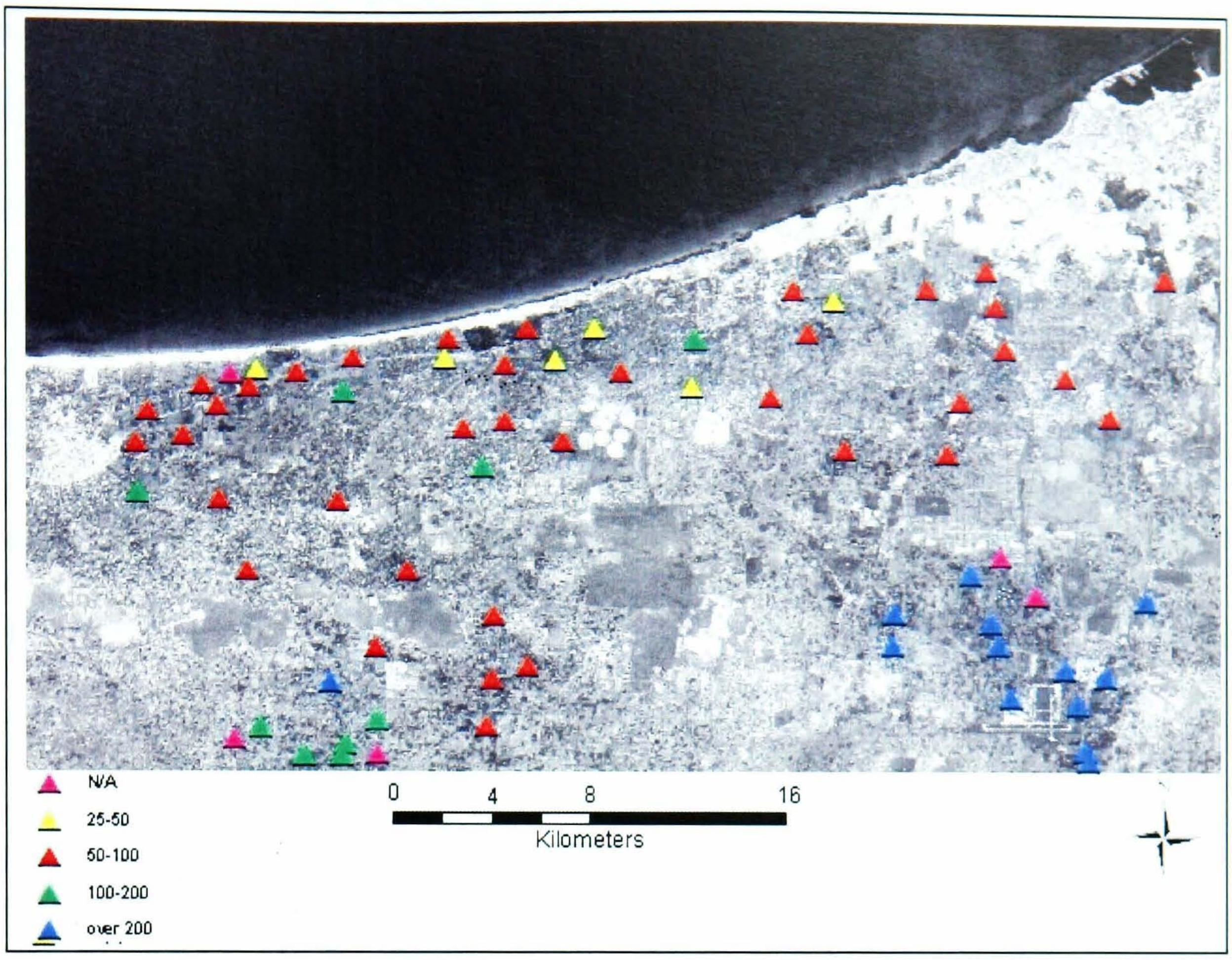

Figure 5.5. Spatial distribution of questionnaire survey responses (groundwater depth in 2000).

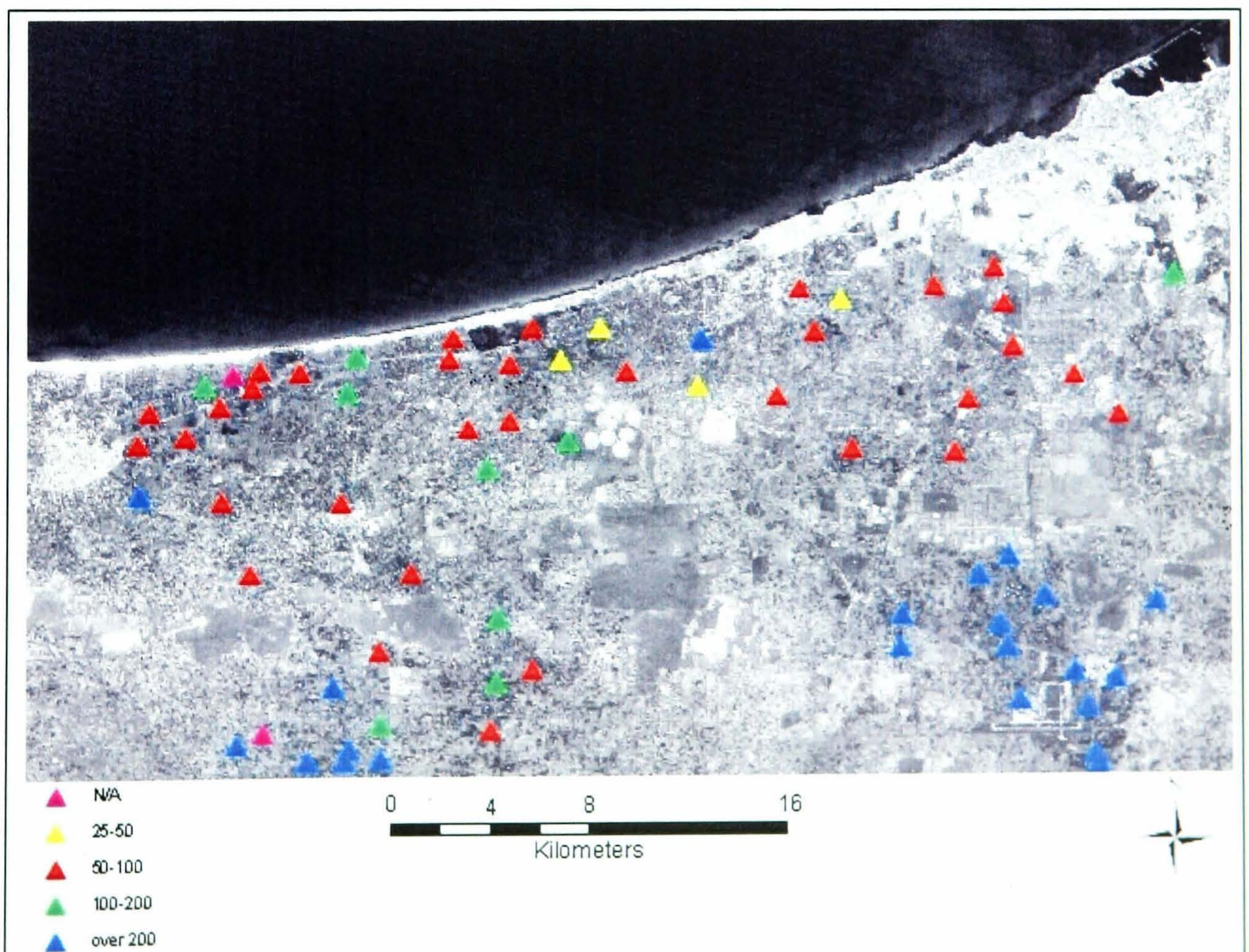

Figure 5.6. Spatial distribution of questionnaire survey responses (groundwater depth in 2006).

In addition, the questionnaire survey responses to Question 8 (Appendix II-B1) illustrate that about 18% of respondents said there was no depletion while 19% noted that there was just some depletion and 56% believed there is a major depletion in the area particularly who resided in the coastal area (Figure 5.7).

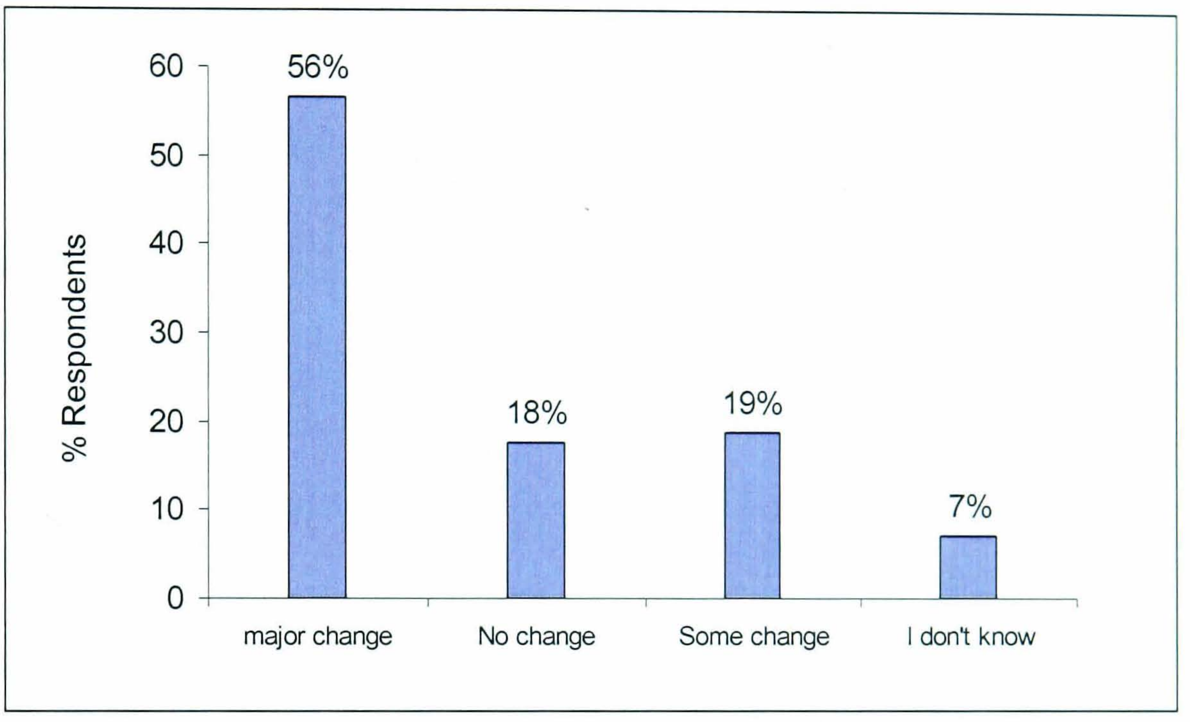

Figure 5.7. Comparison of perceived change in the groundwater depth from 1988 to 2006.

Both questionnaire survey responses and piezometric wells data (Appendix I) illustrate that the groundwater level in the coastal area has not changed as much as in the inland sites. Figures 5.8a, 5.8b, 5.8c, 5.8d and 5.8e show the groundwater depths from different areas of interest in the study area and in particular the difference in the change in the groundwater level in the coastal areas compared to the inland areas. This may be due to saltwater intrusion in the coastal area as the fresh groundwater table falls, and this is investigated further in the questions related to groundwater quality.

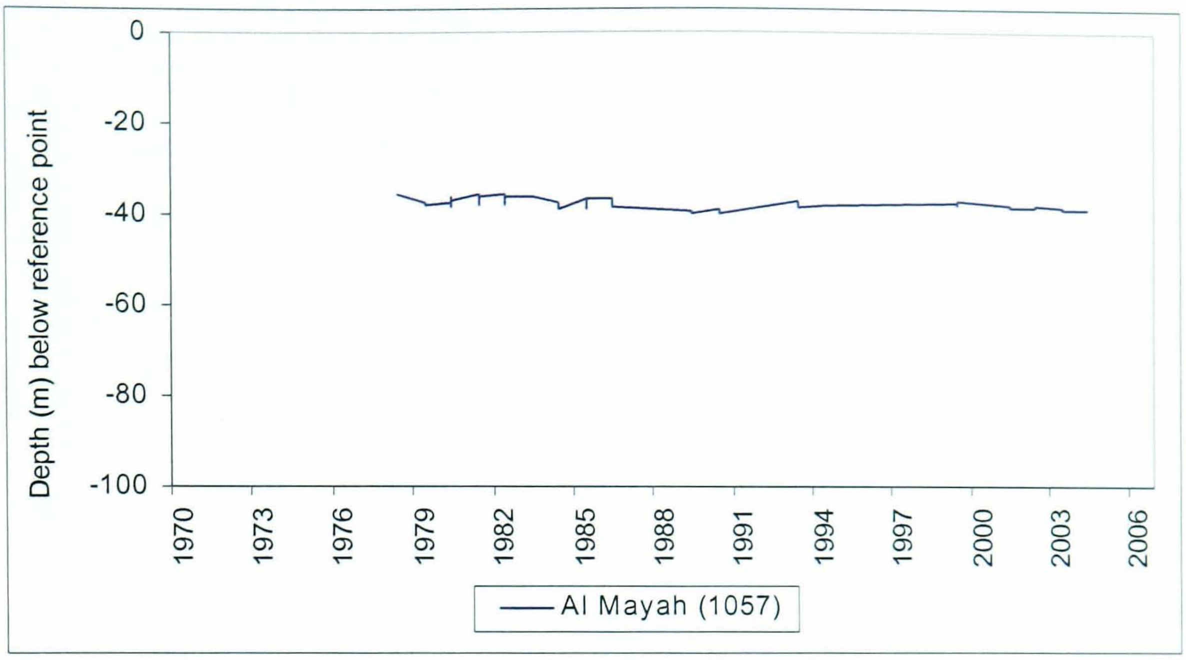

Figure 5.8a. Change in depth of the water table measured by a piezometric well located in Area1.

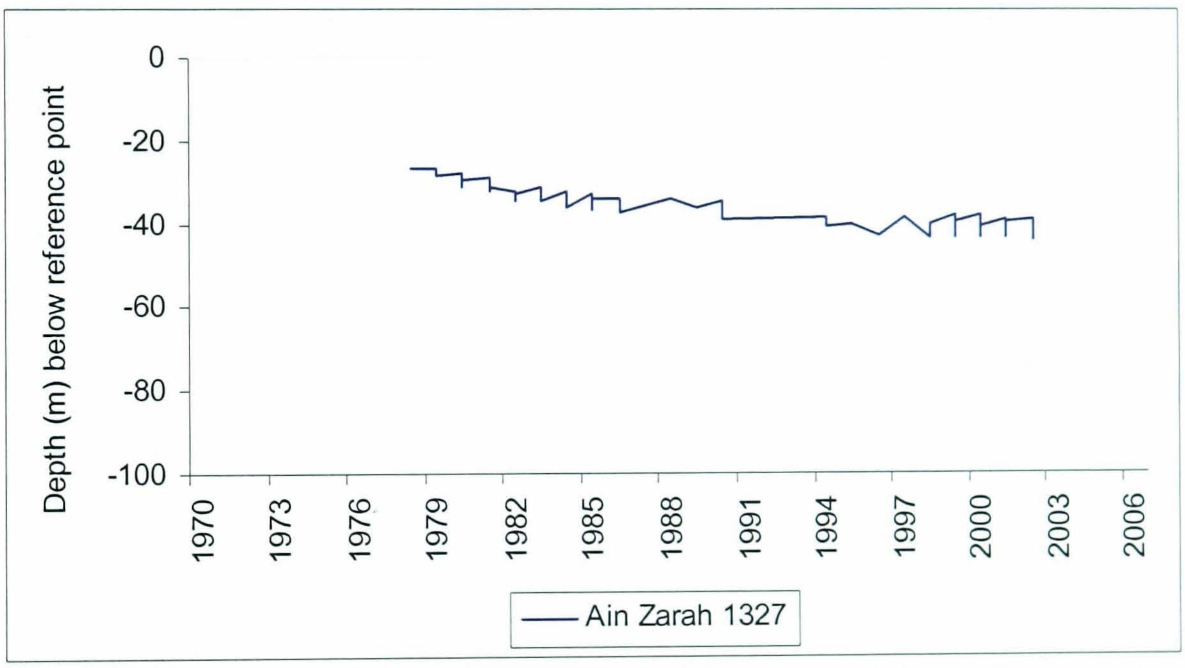

Figure 5.8b. Change in depth of the water table measured by a piezometric well located in Area4.

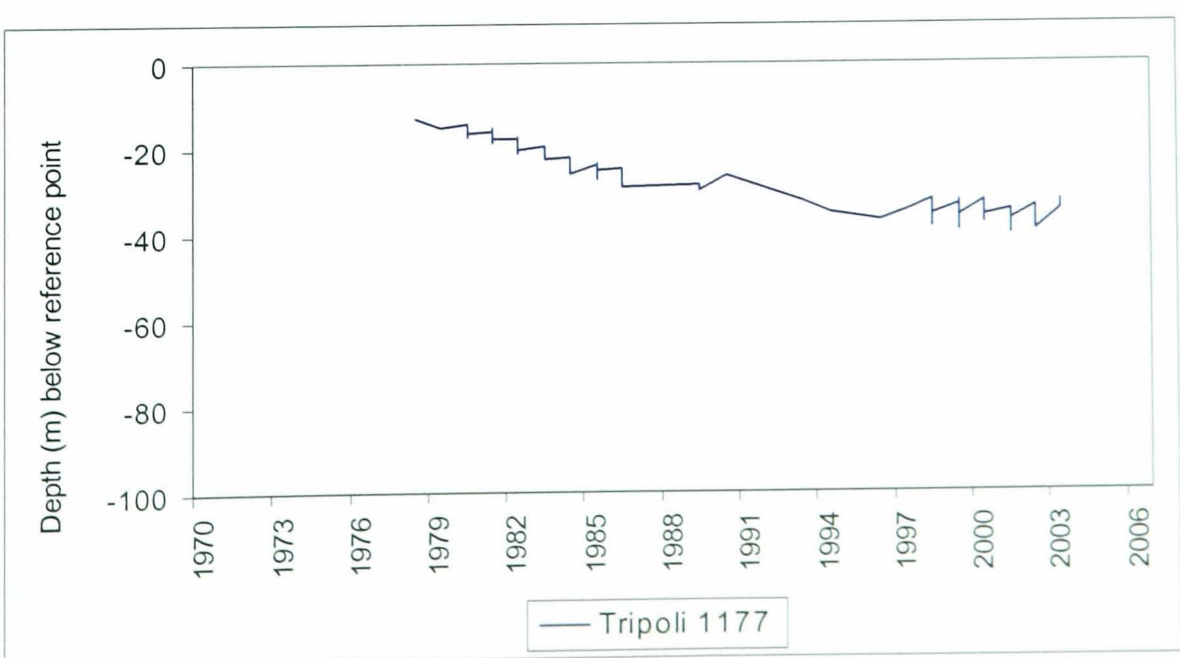

Figure 5.8c. Change in depth of the water table measured by a piezometric well located in Area 4.

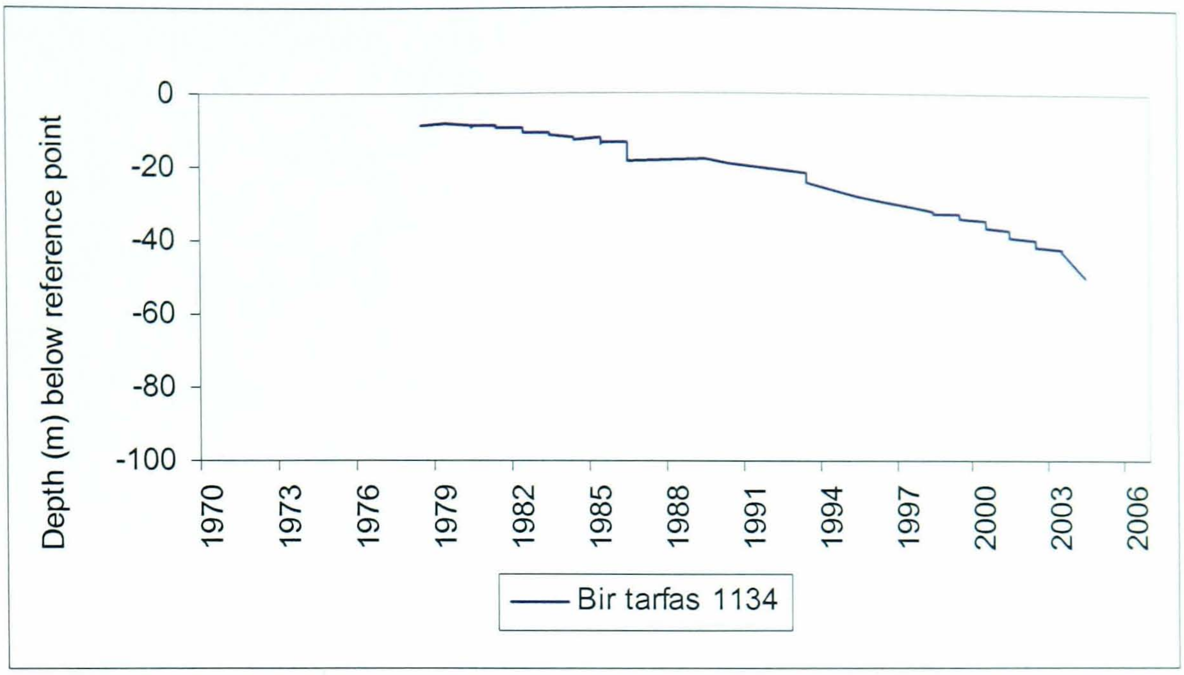

Figure 5.8d. Change in depth of the water table measured by a piezometric well located in Area3.

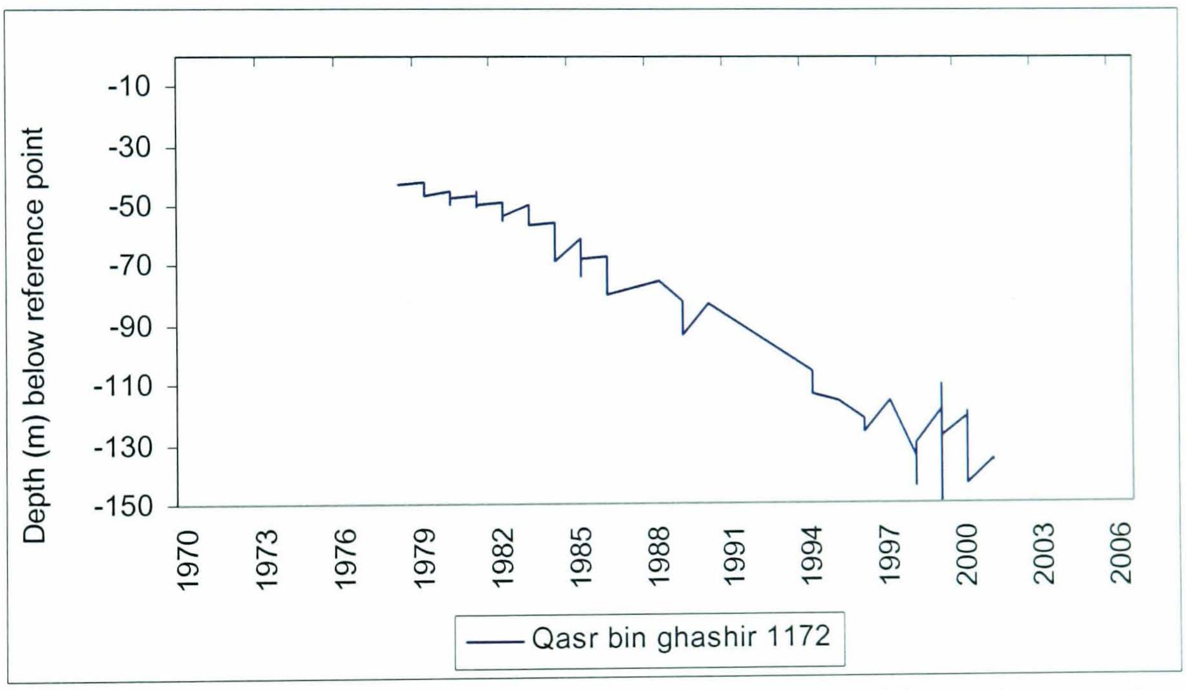

Figure 5.8e. Change in depth of the water table measured by a piezometric well located in Area 5.

Data in Table (5.1) illustrate the change in the groundwater level in all boreholes located in different sits in the study area (coastal and inland). The 12 boreholes have a variable change in the level and more change in the inland areas than the coastal (Figure 5.9), particularly in the southeast of the study area where the farmers more spending more money to keep the water available (informal interviews). In addition, the percentage of the change in boreholes located in the inland area where similar. Figure 5.10 showed the percentage of groundwater level change in different sites (area) in the study area and the different between the coastal areas in inland area.

Table 5.1. The average of groundwater depth from the boreholes in the study area every two years from 1986-2000, and the percentage of change in the depth in 1988 and 2000

	1006	1051	1057	1134	1172	1173	1177	1178	1179	1274	1327	1373
1986	-90.6	-43.2	-38.1	-15.8	-76.3	-76.0	-27.6	-56.7	-55.2	-49.4	-36.6	-36.6
1988	-74.5	-43.0	-39.0	-18.6	-75.7	-76.1	-28.9	-58.6	-55.8	N/A	-34.1	-34.1
1990	-76.7	-43.2	-39.8	-19.2	-83.1	-83.2	-26.5	-60.6	-56.3	N/A	-37.5	-36.7
1992	-81.4	-43.3	-38.6	-20.7	-94.7	N/A	-29.6	-63.2	-56.3	N/A	-38.7	-38.7
1994	-97.6	-43.3	-38.1	-26.4	-113.7	N/A	-35.2	-66.7	-56.9	N/A	-41.0	-39.8
1996	-101.9	-43.4	-38.0	-29.8	-126.6	N/A	-36.9	-70.4	-56.7	N/A	-43.0	-43.0
1998	-96.4	-43.6	-37.9	-32.6	-134.8	N/A	-34.9	-72.3	-57.1	N/A	-43.5	-42.3
2000	-97.5	-43.8	-37.8	-35.3	-144.0	N/A	-36.7	-74.1	-57.3	N/A	-43.0	-41.2
%Δ1988 to 2000	**8**	**1**	**-1**	**124**	**89**	**/**	**33**	**31**	**4**	**/**	**17**	**13**

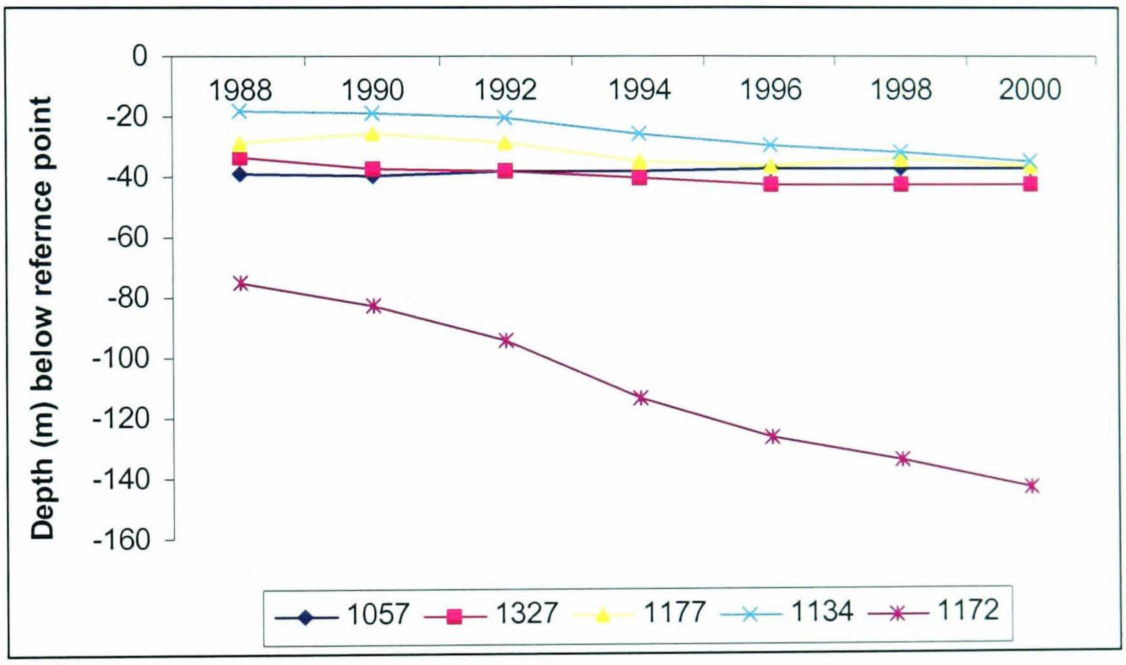

Figure 5.9. Change in the groundwater depth in five boreholes from different sits in the study area.

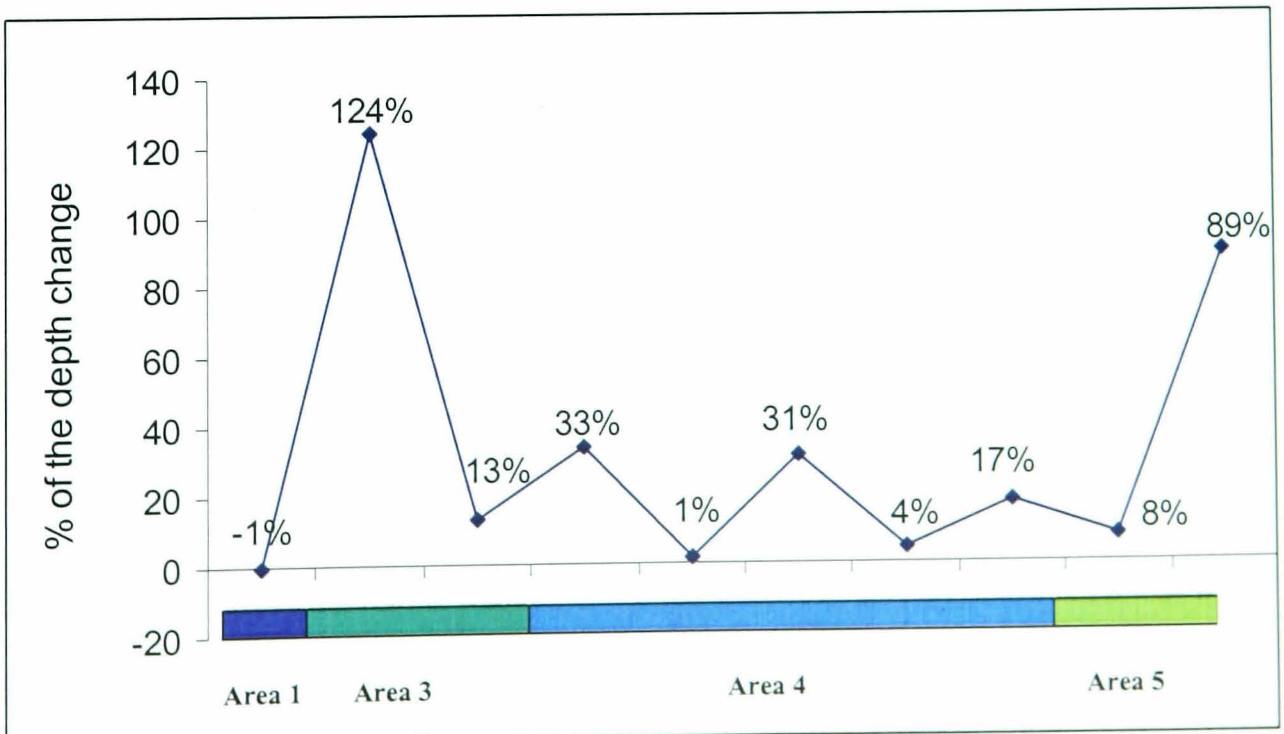

Figure 5.10. Illustrate the percentage of change in different areas in the study area

The questionnaire survey was also used to determine opinion as to the reasons behind the depletion of groundwater levels. The respondents had four choices and the percentage for each answer is shown below:

Intensive use	Less precipitation	Intensive use and less precipitation	Don't know
19%	58%	22%	1%

Whilst this limits respondents to a narrow set of reasons (and clearly other factors may also contribute), the responses suggest that most respondents thought that less precipitation was the main reason for the lack of groundwater recharge and availability, rather than over abstraction.

5.2.2. Groundwater quality

A second objective of the survey was to establish perceived changes in the quality of the groundwater in the region. Initially respondents were presented with six possible answers (*very poor, poor, good, very good, excellent* and *I don't know*) which related to (question four) about water quality in the region over the period from 2000 to 2006. Aquifers in coastal areas, such as the Upper Tripoli aquifer, are vulnerable to seawater intrusion, however, as groundwater levels have dropped in the upper aquifer due to the less precipitation and over-abstraction, well-depths have been extended. In time those wells located near the coast have encountered increasing levels of salinity (El Fleet and Baird, 2001). The Jeffara Plain coastal aquifer can be described only in very general terms; the knowledge of seawater intrusion is still rather limited (Hafi, 1998). Although available data are insufficient for detailed evaluation, the general picture can be described. The responses of questionnaire survey suggest that the perceived quality of groundwater from 2001 to 2006 has deteriorated (Figure 5.11) as well as Figure 5.12 illustrates the seawater intrusion evaluation in the region in the period from 1957 to

1995 and show the change in the groundwater quality particularly in the area along the coastline of the Mediterranean Sea, and some farms in the inland area particularly where the water depth fell to over 200 m in the southeast of the study area (Figure 5.13). In addition, all the respondents noted that the water quality in the 1980s was much better than the present day.

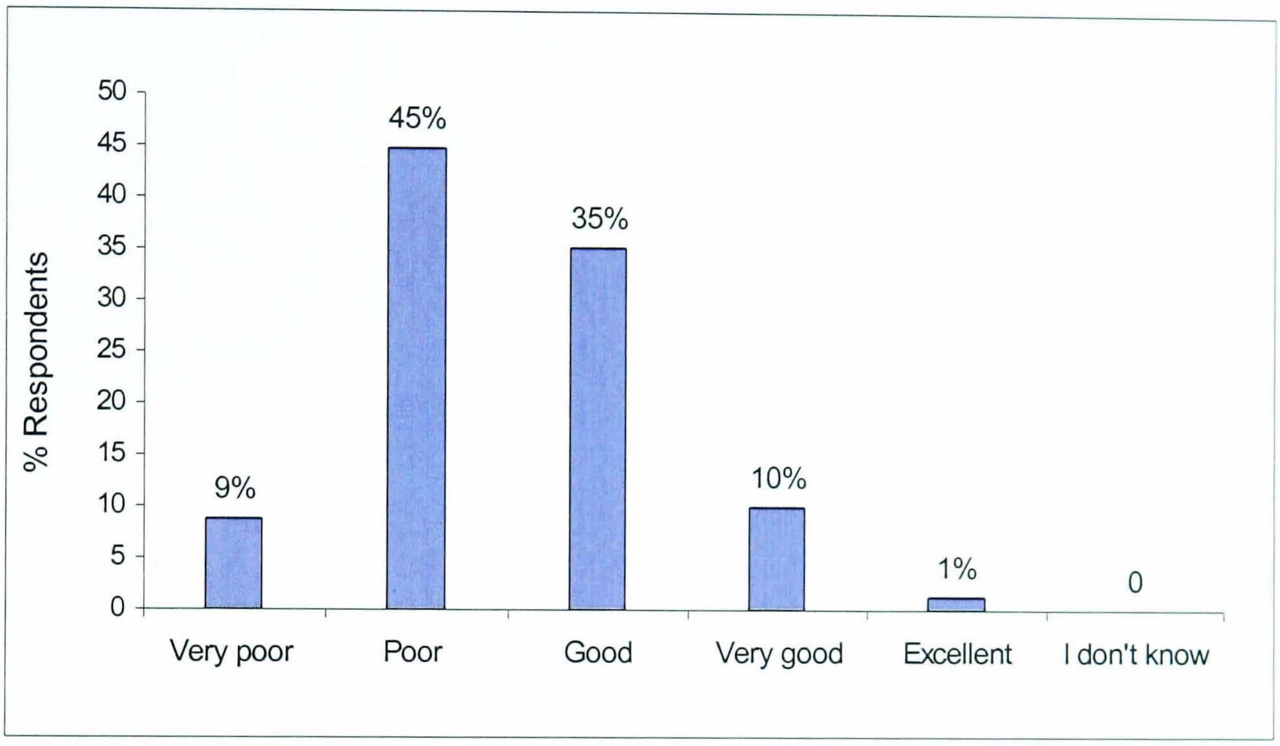

Figure 5.11. Perceived groundwater quality during the period 2000 to 2006.

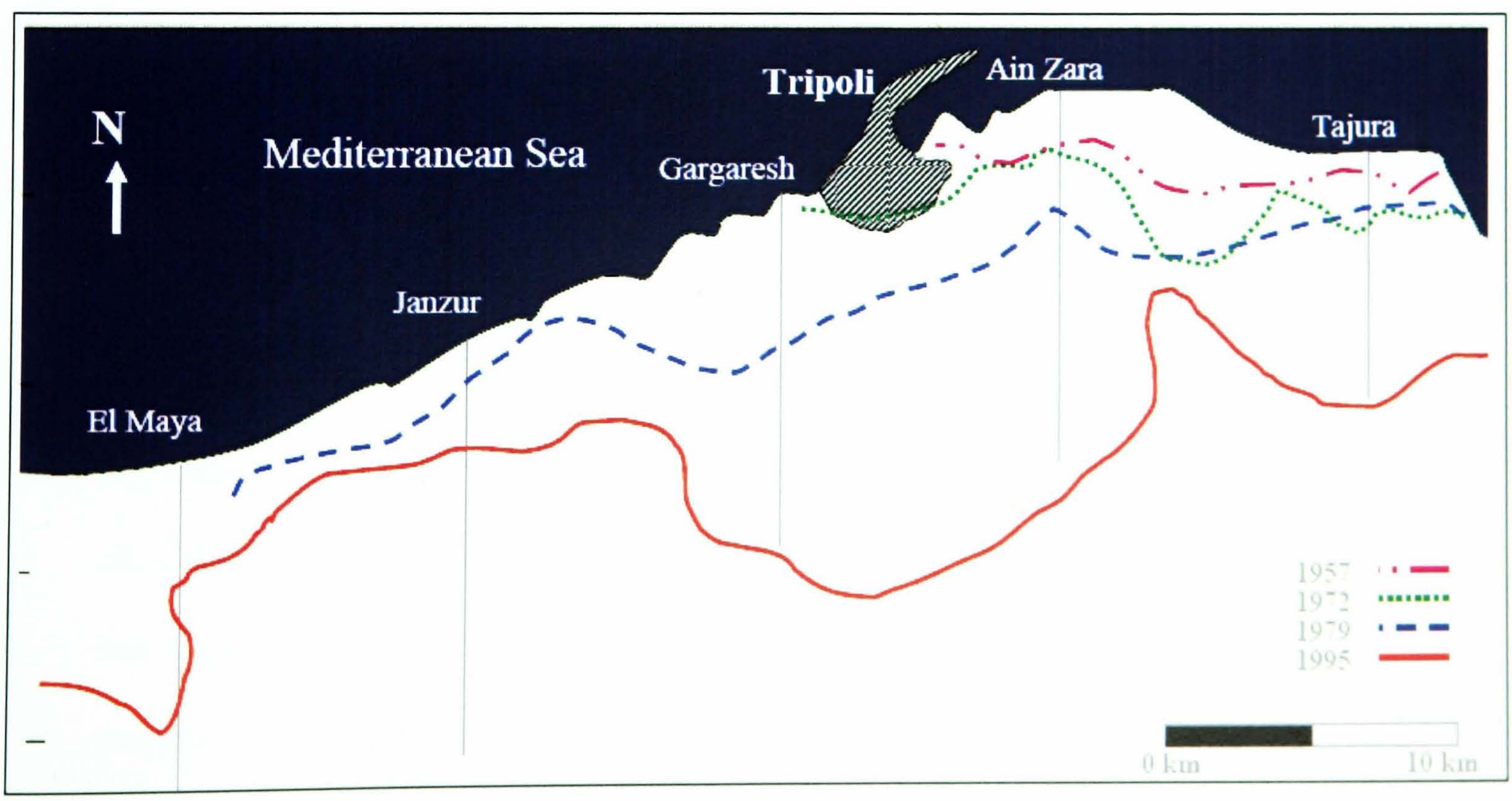

Figure 5.12. Seawater intrusion evaluation from 1957 to 1995,Omar Salem, April 2007

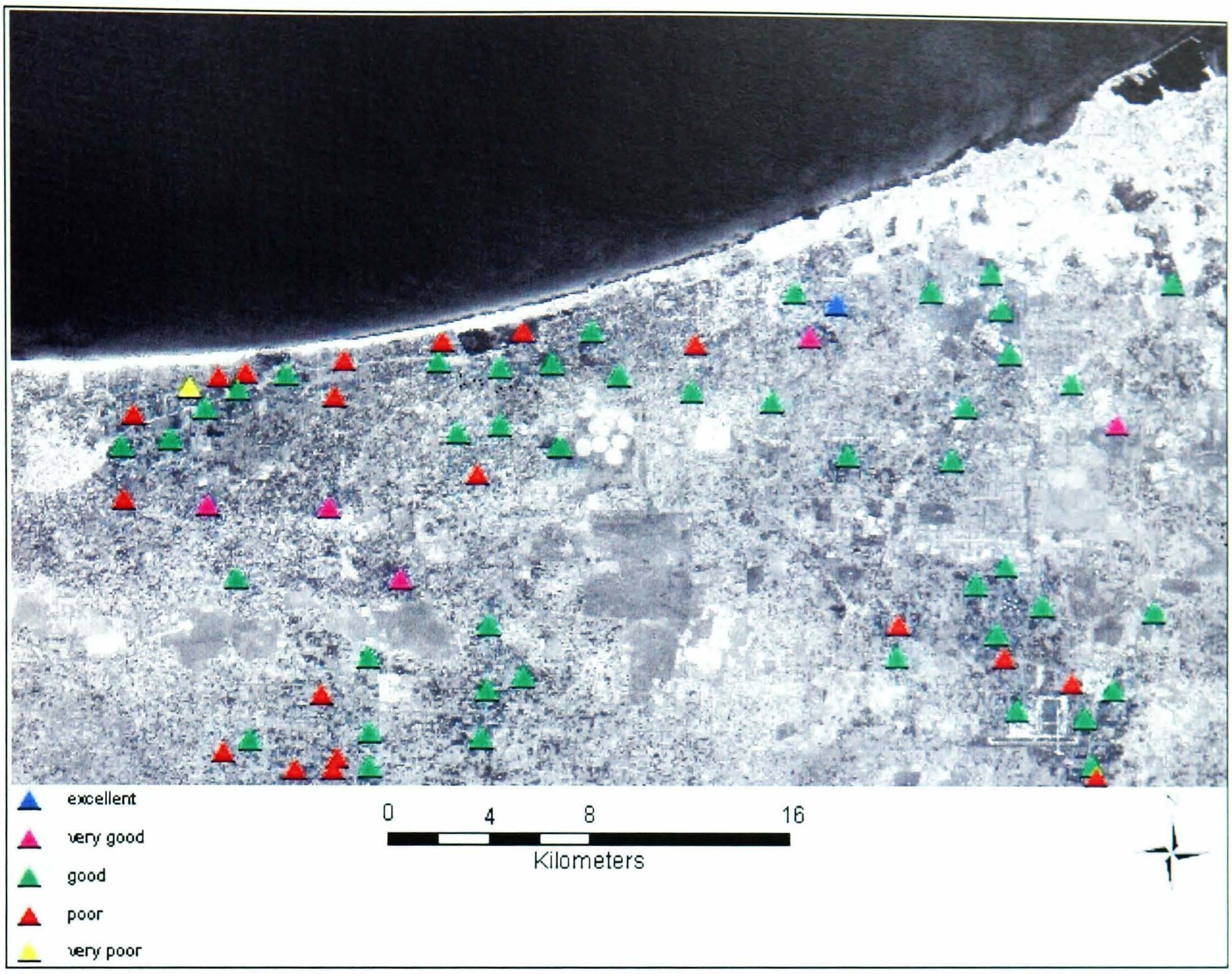

Figure 5.13. Spatial distribution of questionnaire survey responses for water quality in 2006.

5.2.3. Vegetation change

In another category of interest, questions were asked regarding the nature of vegetation types grown in the study area, including crops and trees, the questions and responses were sited from the background knowledge. The orange and olive trees were suggested to be a part of the answers as known the main type of trees from the literature. Also were used to establish if there had been any changes in the types of crops grown during the past 20 years. Respondents were also asked to provide an opinion on the relationship between these changes and groundwater. The first question in this set related to the main types of vegetation grown in the region and asked respondents to identify the main types of agricultural crops and trees grown. The percentage responses given by the farmers were as follows:

Citrus fruits	Citrus fruits and olive trees	Olive trees, annual crops and citrus fruits	Different kinds of trees and annual crops
24%	30%	19%	27%

It is observed that citrus fruits and olive trees are the main types of trees grown in the region, but there are also other types of trees grown, for example, palm trees, fig trees and peach trees. Different types of annual crops are grown either independently or sometimes between the lines of trees. A further question was posed to establish if there had been any change in these types of vegetation.

Has the pattern and types of crops/trees grown in this area changed during the past 20 years?

The responses to this question (Figure 5.14) show that there has been a perceived change in the types of vegetation/crops that are grown, in comparison to the past 20 years. Some 49% of the respondents agreed that there had been a change in the pattern and type of vegetation, with 24% disagreeing. Some farmers commented through informal interview that these changes occurred particularly in citrus fruit-growing, especially orange trees, as they needed more water to irrigate them. One respondent said, "We are trying to grow another type of tree that does not need a lot of water, such as palm trees." (Farm D). Figures 5.15 and 5.16 show fig and palm trees of different ages, and some of them have been recently planted.

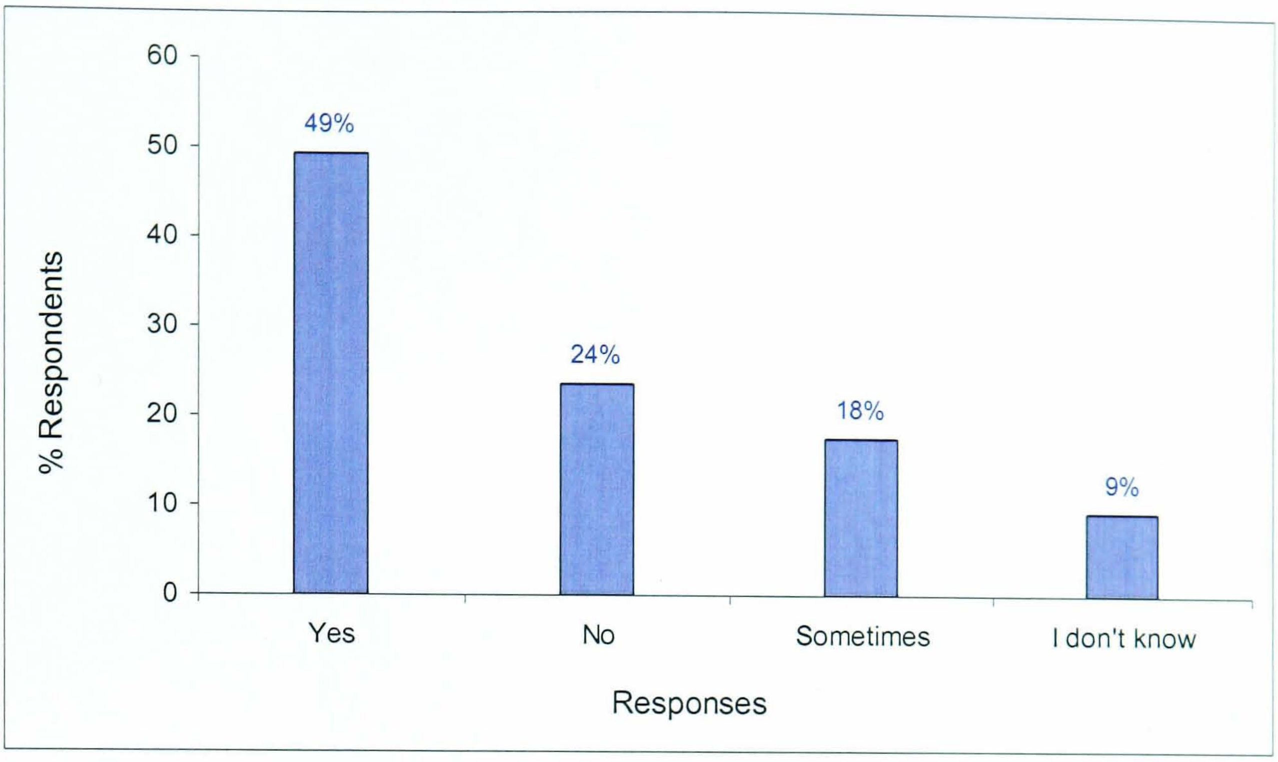

Figure 5.14. Responses to the question asking whether the pattern and types of crops/trees grown in the area had changed over the last 20 years.

Figure 5.15. Palm trees being grown instead of citrus fruits (Farm D), 5th July 2006.

Figure 5.16. Fig trees being grown instead of citrus fruit trees (Farm D), 5th July 2006.

Anticipating such change, the following question was asked about the relationship between the changes in the groundwater level and the changes in the types of vegetation (trees/crops) grown in the area:

Do you believe the change of the type trees/crops is related to groundwater?

Most answers illustrate that farmers perceived a relationship between the changes in the type of vegetation and changes in the groundwater in the region (Figure 5.17), with many echoing the following observation: "The trees, especially the orange trees, need to be irrigated during the whole year and there is not sufficient water. If we keep growing this kind of trees the wells have to be re-dug every 3–5 years and that is not economical, so this is one of the most important reasons to stop growing these kind of trees" (Farm A).

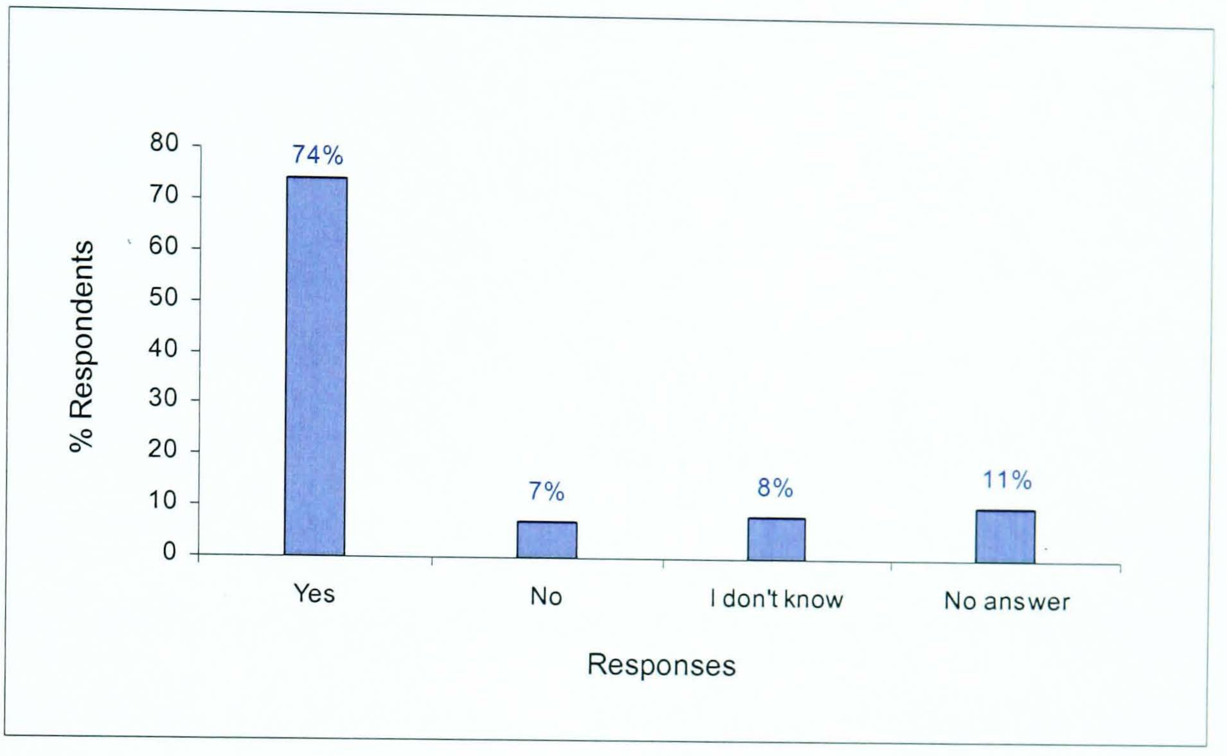

Figure 5.17. Responses to the question asking whether respondents thought there was a link between vegetation type and groundwater status.

Finally, the questionnaire included a section where farmers could add any comment about issues not covered by the questions provided. In many cases, however, respondents offered the same comments as those recorded during the informal interviews which had already been carried out. For example, some of the respondents noted that in some places the groundwater level dropped to between 280 and 350 m, and that the vegetation cover had died, particularly the orange trees. Also, a number of farmers linked the change in water quality (i.e. hot, salty water with sulphurous odour) to the major change in the depth of the groundwater level which has had an indirect effect on the trees and crops in the area. In addition, some farmers noted that as result of groundwater availability (i.e. water scarcity), many farmers have decided to stop agricultural activities altogether. Some comments referred to the cost of the water supply, with one of the farmers commenting that, "the fall of the groundwater level is about 1 to 1.5 m/year and to re-dig the well (borehole) will cost more money, which is uneconomical" (Farm G).

5.3. Discussion of questionnaire survey results

The analysis of the questionnaire survey by comparing the responses to each question, along with informal comments from the farmers, the following important points can be highlighted. By comparing responses regarding the groundwater level in the study area during the last 20 years with the hydrological data provided by piezometric wells; there is general agreement between the datasets which illustrate a severe decline in groundwater levels (Figure 5.8d and e). Changes in the groundwater level differ from one place to another, and in some places, such as the coastal areas, it has remained at a similar level (Figure 5.8a, b and c). Also there is an apparent relationship between the changes in the groundwater level and the changes in the vegetation cover, with the change to crops requiring less water being a key example.

Due to the water table level dropping progressively, the cost of digging or re-digging wells has increased as deeper wells need to be dug. As a result, agricultural activities have changed toward the cultivation of tree species which require less water and are, therefore, more economical, and the quality of groundwater is becoming poorer in some areas. This is due largely to groundwater lowering particularly in the coastal area and subsequent saline intrusion. Respondents believed that the change in the agricultural activities in these areas was related to the change in groundwater quantity, rather than quality.

A high percentage (over 50%) of responses reported that orange trees and olive trees were the main types of trees grown in the area when the groundwater was available in sufficient quantities, but these have changed to other crop types since the groundwater has lowered. In addition, the responses to the questions and the informal comments show that, in general, the land cover types are the same, but clearly the patterns of growth and extents of each land cover type have changed.

5.4. Possible surface effects of groundwater lowering

The general view of the information collected from the questionnaire survey and informal interviews with farmers confirmed the significant effects on the land surface (vegetation cover) that groundwater changes have had in the study area. These effects can be categorized into either direct or indirect effects, as follows:

Direct effects

• As a direct effect of the groundwater changes, the types of trees and crops grown in the study area have changed. Palm trees are one of the species which are well-suited to the current groundwater conditions in some areas, and are now being grown on most farms (e.g. Figure 5.15).

• Another direct effect was that on many farms in the study area where groundwater had become insufficient to irrigate the main type of trees previously grown in the area (orange trees), the farmers decided to stop growing such crops. The photographs in Figure 5.18 are all from Farm A where the owner reported that in the 1980s the orange trees covered an area of approximately 7 ha (Photo 1) as the groundwater was sufficient (water table depth between 25-50 m). However, because the water table has fallen to a depth of over 200 m, a decision was made to reduce the area of orange trees under cultivation since they needed a lot of water. Even those that were left died (Photo 3). Thus, most of the area was converted to growing annual crops and the area now under orange tree cultivation covers less than 1.5 ha (Photo 4).

• The other effect of groundwater lowering, as determined from the questionnaire survey responses and the comments of the farmers, is land degradation (desertification). This is especially so in coastal areas where water quality has deteriorated due to saline intrusion. In this region the vegetation cover has dried out, remaining alive but clearly stressed, and with evidence of chlorosis and reduced canopy cover. This includes areas of semi-natural vegetation, as well as cultivated areas, and can lead to desertification and loss of biodiversity (Ben Mahmoud *et al.,* 2000).

Indirect effects

• Due to the fall in the water table, some farmers have re-dug and/or dug new wells to try to find enough supplies, e.g. Farm F (Figure 5.19).

• The groundwater in coastal areas has become saline extending to areas over 200 m inland. Furthermore, the water in such areas has become very hot and salty water with sulphurous odour e.g. Farms B, G (Questionnaire survey). In some farms in Area 3, vegetation (trees / crops) have died, as groundwater supplies are not of sufficient with poor water quality to be used for irrigation purposes (Figure 5.20).

• A further indirect impact of groundwater lowering is that when the environment around the trees becomes dry, this provides ideal conditions for fungal attachment along with other diseases (e.g. Fungal Plant Disease) (farmer's comments) (Farm B), which can result in trees dying (Figure 5.21a & 5.21b).

Figure 5.18. Farm A, (1) Orange trees still being grown; (2, 3) Orange trees cut; (4) Area converted to grow annual crops that have recently been harvested (visited on 9th July 2006).

Figure 5.19. Farm F, on 12th June 2006, (A,B,C) Re- digging a well to over 159 m but still yielding insufficient groundwater. (D) The well after it has been re-dug.

Figure 5.20. One of the farms in Area 3 where vegetation has suffered/died from water shortage with poor quality which has been used to irrigate the crops. The owner has now decided to stop growing any kinds of trees (9th July 2006).

Figure 5.21a. Diseased orange trees (e.g. Fungal Plant Disease) due to the dry environment (Farm B), 9th July 2006.

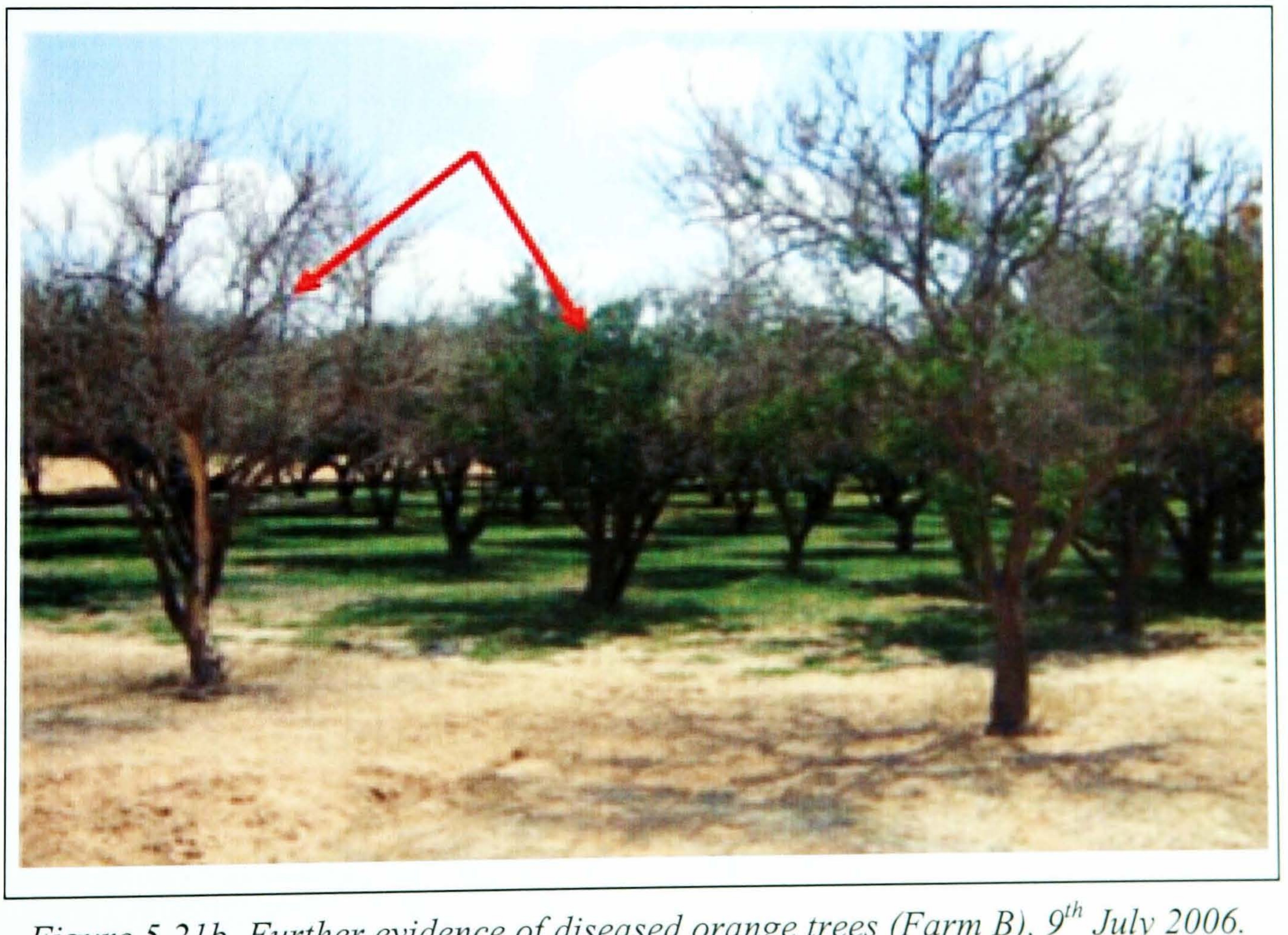

Figure 5.21b. Further evidence of diseased orange trees (Farm B), 9th July 2006.

5.5. Summary

As a result of visiting the study area, conducting the questionnaire survey, and interviewing local farmers, it is clear that groundwater changes (quantity and quality) have had a significant impact upon the vegetation cover and agricultural activities of the area. A pertinent summary of what the farmers noted in general is that, "The impact can be a direct impact upon the vegetation itself, or it can be related to indirect economic reasons; for instance the increasing cost of using groundwater for irrigation when the groundwater level deepened and wells had to be re-dug, which was not economically viable" (the owner of Farm F).

There is visibly a huge land cover `signal` in the lowering of groundwater (either by direct or indirect effects). With such anecdotal changes (as observed with the questionnaires), a more formal assessment is required, and therefore, the following chapter will focus on the classification of remote sensing data to quantify these changes. The questionnaire survey has clearly demonstrated a link between groundwater and land cover/agricultural production.

CHAPTER SIX

Landcover change characterisation using maximum likelihood classification

6.1. Introduction

In Libya groundwater is the main source of water supply for both irrigation and drinking water (EMWIS, 2005; Pallas, 1980). Furthermore, groundwater is important for agriculture, for both irrigated and natural vegetation growth (Le Maitre *et al.,* 1999). The past three decades have seen a decline of the groundwater level in the study area. The previous chapter highlighted that there is an apparent or perceived relationship between the status of groundwater (availability and quality) and the kinds of crops grown (and hence land cover) in the Jeffara Plain region of Libya.

To confirm the extent of land cover change that may be directly attributable to groundwater change, the aim of this chapter is to assess the extent of changes in vegetation cover over the period 1988 to 2000, using Landsat TM5 images. Image classification was applied to a series of images from different dates to identify changes (and rate of change) particularly in the vegetation cover classes, rather than producing a complete land cover map with all possible land cover classes included.

6.2. Image classification

As stated in Chapter Two, there are different techniques to detect land cover changes from remotely sensed data (Mas, 1999). Greatest accuracy was obtained using post-classification comparison based on supervised classification using a maximum likelihood algorithm. Given the demonstrable success of Mas (1999) and others, a supervised classification technique was used in this project to identify changes in the vegetation classes which might be related to groundwater lowering.

Maximum likelihood (ML), used as part of a 'traditional hard' classification approach, is one of the most common classification algorithms to locate land cover changes using multitemporal satellite imagery (Mclver and Friedl, 2002; Richards, 1993). The method adopted to determine and analyse change here was the same but with the use of high spatial resolution data (Quick Bird 2002, SPOT5 2002 and SPOT XS 1987) and other ancillary data, such as maps and questionnaire responses, to aid selection of training samples and assess the accuracy of the land cover maps produced.

6.2.1. Definition of land cover classes

Land use and vegetation maps have been the subject of several national and international projects in World. One of them is the Corine Land Cover (CLC) project which established in 1985 by the European United (EU), the purpose was to generate a homogeneous European map of land use at a 1:100 000 scale and to create pan-European databases on land cover, biotopes (habitats), soil maps and acid rain. Corine stands for *Coordination of Information on the Environment*. Corine. Whilst, the purpose of the classification in this research was to identify those land cover classes that were relevant and likely to be affected by groundwater lowering, rather than to produce a map of all land cover classes present in the area, hence a subset of relevant classes had to be identified. Therefore, an existing (1981) land use map of the study area (Figure 6.1) was used as a reference to identify all previously mapped land cover classes in the area rather following Corine program. The legend of the map as shown in Figure 6.1 is not readable, therefore the recreated to be readable (Table 6.1). In addition, the questionnaire survey responses (in Section 5.2) helped to identify the vegetation classes that appeared to have been most affected by change in groundwater status.

Both the map and the information derived from the responses confirmed that citrus fruits and olive trees are the most common vegetation types grown in the area, as well as annual crops such as cereals and alfalfa.

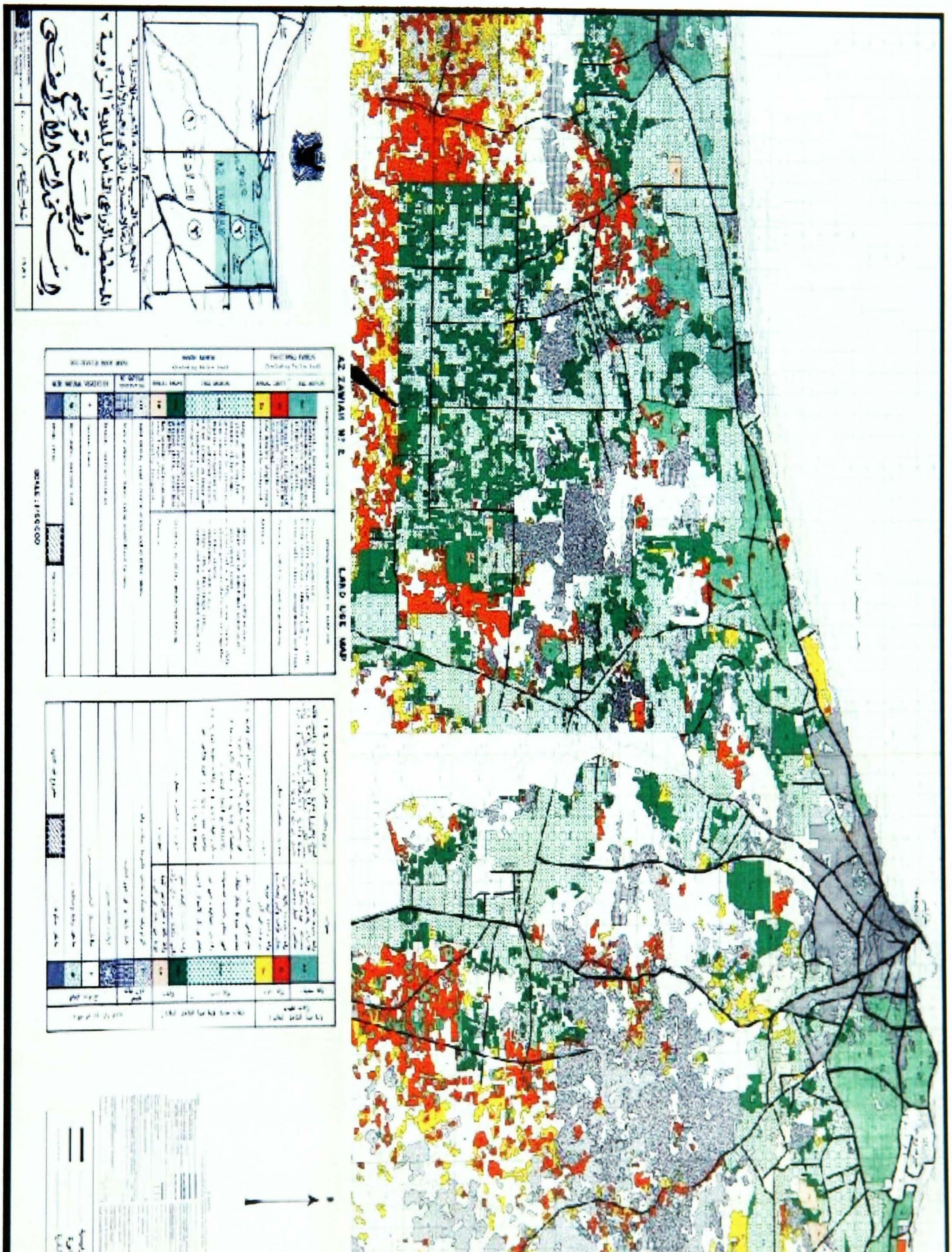

Figure 6.1. Mosaic of 4 sheets of land use maps of the study area (1:50000) Land use map (1981) (Ministry of agriculture-Libya).

Table 6.1. Recreated legend of the land use map (1981).

		CHARACTERISTICS OF FACIES		SPACIAL BREAKDOWN OF LAND USE
TRADITIONAL FARMING (including fallow land)	TREE GROWING	**Aci**	Generally heterogeneous plantations usually associated with multiple crops which are sometimes irrigated: alfalfa, market-gardening, cereals.	Frequently intermixed: Olives (32%), Palms (26%), Fruit Trees (8%), Citrus Fruits (4%), Almonds (2%), occasionally vines, pomegranates and figs.
	ANNUAL CROPS	**Ci**	Intensive cultivation of diverse crops, sometimes irrigated (boreholes and pumping)	Cereals, alfalfa, market-gardening
		Cs	Low density single crops, occasionally irrigated.	Cereals
MODERN FARMING (including fallow land)	TREE GROWING	**Acrm**	Large geometrical plots planted in a regular manner, either homogeneous or in association with other crops. Regular irrigation for citrus and other fruits either grown on their own or together; occasional irrigation in all cases.	-Olive (51%), Almonds (8%) either on their own or sometimes associated with cereal crops. -Citrus fruits (51%), other fruits (5%), either grown on their own or together or with olives (17%) -Occasional vines (1%), crops (10%), buildings (1%), roads and non cultivated areas (8%)
	ANNUAL CROPS	**Cim**	Intensive cultivation of diverse crops, regularly straped plots, sometimes irrigated.	Cereals, alfalfa, market-gardening
		Cm	Low density cultivation; very large plots, occasionally.	Cereals
UNCULTIVATED SANDY AREAS	NO NATURAL VEGETATION	**Dvs**	Sand dunes, sand covered areas and drifted sand.	
		Dvm	Stable dunes or dunes being stabilized by man.	
	WITH NATURAL VEGETATION	**F**	Forest, reafforestion	
		P	Pasture land.	
		W	Wet-lands, pasture land	
			Urban area	Agricultural project

From this analysis, five vegetation classes were identified that are likely to be impacted significantly by changing groundwater status (Classes 1, 2, 3, 5 and 7, Table 6.2). Several other land cover classes found across the Jeffara Plain were also included in the classification (Classes 4, 6, 8 and 9), and although they are likely to be unaffected by groundwater change, were included to avoid spectral overlap/mis-classification.

Table 6.2. Land cover classes estimated from the remotely sensed images.

Classes	Class definition
Class 1	Other trees **(OT)** which includes mixture of different tree types, typically grown together in small fields/plots (e.g. Olive, Palm, Grape and Almonds)
Class 2	Citrus fruits **(CF)** (Orange and Lemon)
Class 3	Annual Crops **(AC)** (Cereal, alfalfa, market-gardening, etc.)
Class 4	Urban areas **(U)**
Class 5	Pasture land with semi-natural vegetation **(PLNV)**
Class 6	Bare soil **(BS)**
Class 7	Forest **(F)**
Class 8	Sea **(S)**
Class 9	Bare rocks **(BR)**

Class 1 comprises different types of trees, referred to as 'Other Trees' (OT). These trees are not necessarily spectrally similar but since many of the fields on the farms in the study area are small and often contain a 'cocktail' of different types of trees in a small area, it would be very difficult to classify these individually into separate classes (Figure 6.2). This class also refers to fields that have only olive trees grown in regular lines with spaces (soil) between the lines of trees (Figure 6.2B and 6.2D). While other fields have a mixture of different trees (some including olive trees), these crops are not grown in lines and the spaces between them are not standard (Figure 6.2A and 6.2C). Therefore, fields which contain solely olive trees or mixed tree crops (e.g. olive, palm, almonds, pear, and fig) have been classified as Class 1.

Figure 6.2. Examples of 'Other Trees' class (OT). Only olive trees (B and D) or mixed with other trees: olive, palm, almonds, and apricot trees (A and C). This photo was taken 5th July 2006.

Orange and lemon trees comprise the citrus fruit class (CF). It is different from the previous class (OT) in that the trees are grown in different arrangements within fields and are grown separately from other tree crops (rather than mixed within a field). It is common for there to be a variety of different tree sizes present within a single field (Figure 6.3A and 6.3B), which are mostly grown in rows but with variable spacing between the rows (Figure 6.3C and 6.3D). Class 3 represents fields with a variety of different annual crops (AC), sometimes referred to as areas of market gardens. These tend to be small fields and often with a variety of different vegetable crops present (Figure 6.4B), as well as cereal crops (Figure 6.4A) and alfalfa (Figure 6.4C), which may be grown in larger fields.

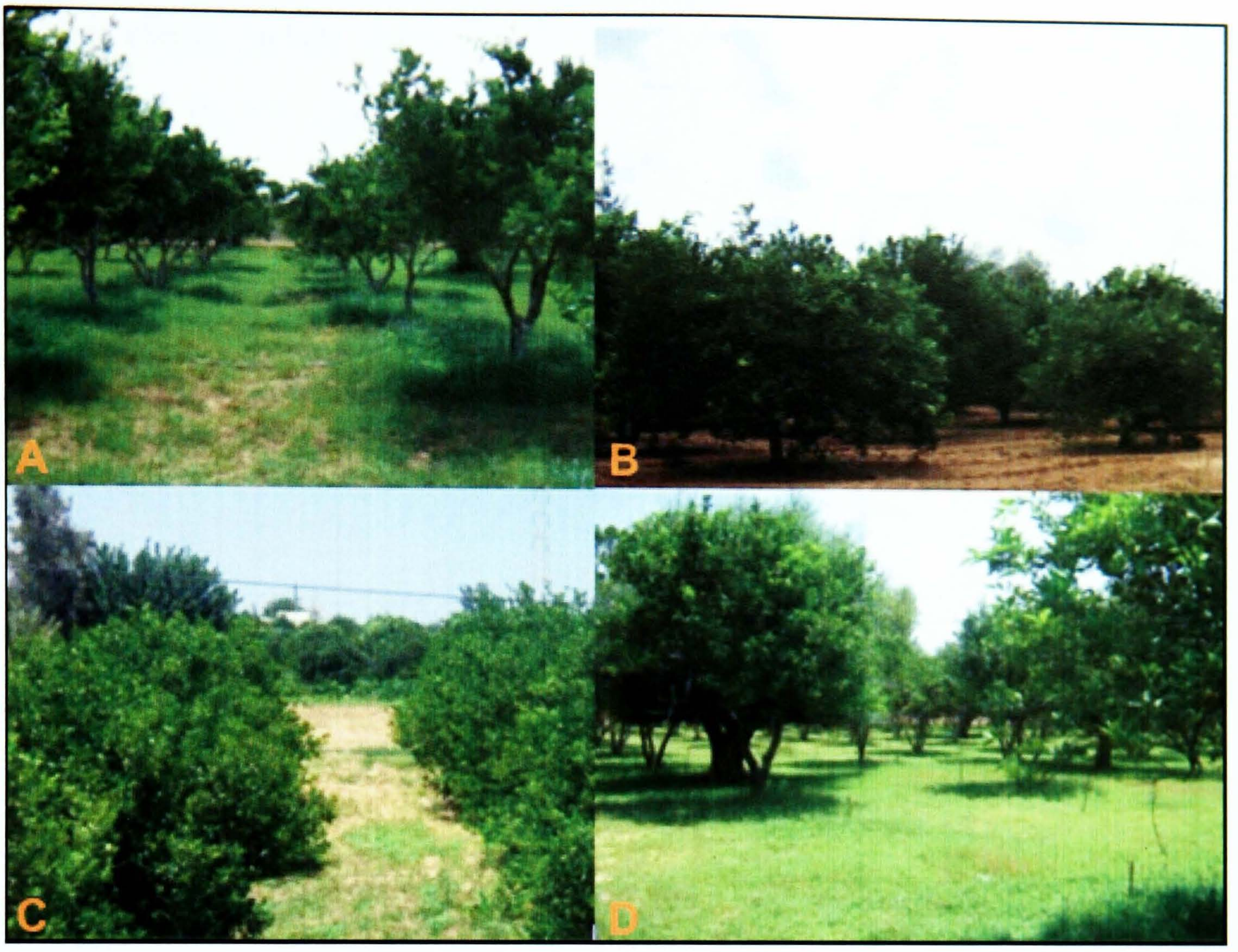

Figure 6.3. Different fields planted with orange and lemon trees (Class 2), Photos A and B show a pattern of orange trees of different sizes; Photos C and D illustrate fields of orange trees with different spacing between the rows. This photo was taken 5th July 2006.

Figure 6.4. Fields used to grow different annual crops (Class 3); Photo A cereal crop, Photo B market-gardening, and Photo C alfalfa. This photo was taken 7th July 2006.

Other classes include urban areas (UA, Class 4), pasture land with semi-natural vegetation (PLNV, Class 5), bare soil (bare land) including ploughed fields, areas planted with arable crops and new plantations areas (BS, Class 6), forest and areas of reforestation (F, Class 7), and sea (S, Class 8). Bare rock (BR), which tends to occur mostly along the coastline due to extensive quarrying, can also be found in other non-cultivated areas, was included as Class 9.

Classes 1,2 and 3 (OT, CF and AC) are the most interesting vegetation classes in the analysis, as these are mainly irrigated from groundwater sources, while Class 5 (PLNV) relies purely on groundwater as a source of moisture in arid and semiarid areas (Xu *et al.,* 2007). It is likely, therefore, that changes in these land cover types will be more dependent upon groundwater availability than other land cover types, such as urban areas and bare rock, and so the detailed analysis of change in extent was limited to these classes only.

6.2.2. Obtaining training samples

There are three steps to the image classification process: training, classification and testing (Lillesand *et al.*, 2004). Training samples were selected randomly from across the image to minimise spatial autocorrelation, i.e. the likelihood that samples collected close together are more similar than those from further away, thus minimising within class spectral variation and a possible source of confusion and mis-classification (Rogan *et al.,* 2002). Using the ML algorithm, a key concern is the number of training datasets that represent each class (Mather, 2004; Piper, 1992), while the training sets statistics represent all spectral classes comprising the information for each class to achieve optimal accuracy, which depends upon the discrimination wavebands (Lillesand *et al.*, 2004). Therefore, between 100 and 110 independent training sets per class were collected, with each training sample containing between 15 and 40 training pixels in total. The training samples were extracted manually by digitizing a polygon covering an area of known land cover. These were detected by visual analysis with reference to the land use map, field survey and local knowledge, plus consultation of the high spatial resolution data (QuickBird and SPOT 5).

Some classes in the study area have a very similar visual appearance in the images, with some vegetation classes being spectrally similar. For example Classes 1, 2 and 3, OT, CF and AC, have similar radiance values, particularly in visible wavebands (Figure 6.5).

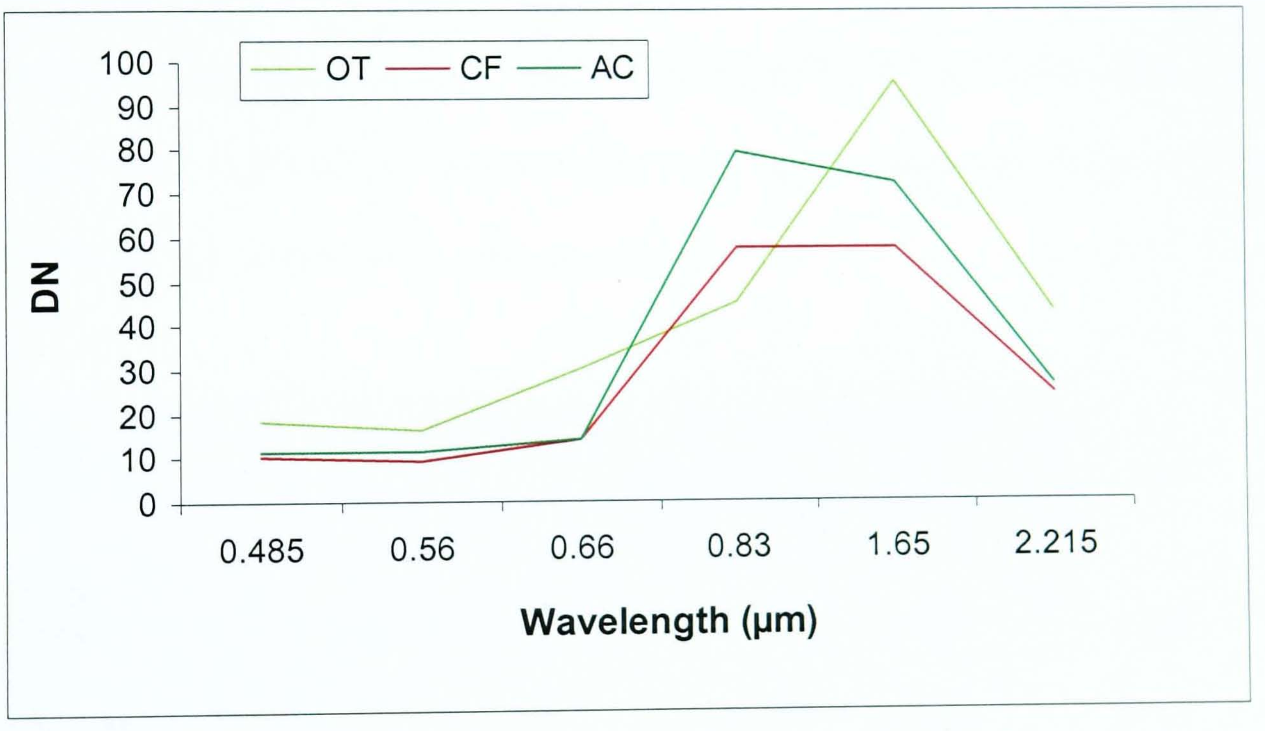

Figure 6.5. Spectral profile for classes OT, CF and AC.

Both visual interpretation of the composite image and background knowledge of the area were used to obtain 100 training regions (15-40 pixels in each region) for each class to classify the 1988 Landsat TM5 image initially. To classify the other Landsat TM5 images (1992, 1996, and 2000), the process was repeated and approximately the same number of samples again collected randomly across each image. To aid collection of samples for the most recent image, a visual interpretation of the Quick Bird (2002) and SPOT5 (2002) was used to identify different land cover class locations.

6.2.3. Classification procedure

The Maximum Likelihood classifier was used to classify the Landsat TM5 data (each image separately) of the study area using all wavebands except the thermal waveband (band 6). The ERDAS imagine image processing software was used to implement the classification.

6.3. Classification results

The results of the classification (Figures 6.6 to 6.9) were analysed through the post-classification comparison analysis to locate the change in the land cover classes in the study area (Mas, 1999). Then, direct attention was given to changes in the vegetation classes OT, CF, AC and PLNV in particular.

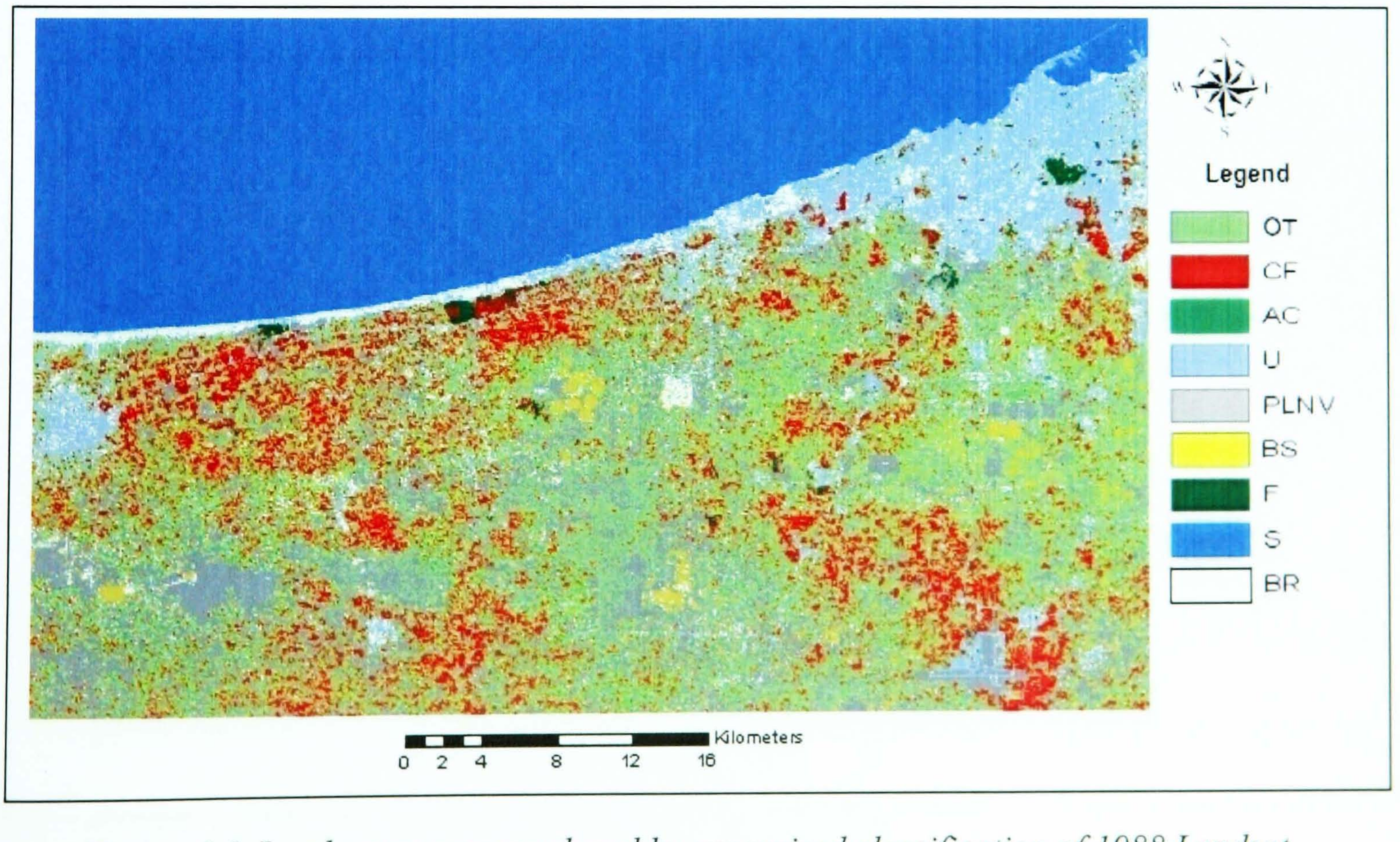

Figure 6.6. Land cover map produced by supervised classification of 1988 Landsat TM5 image.

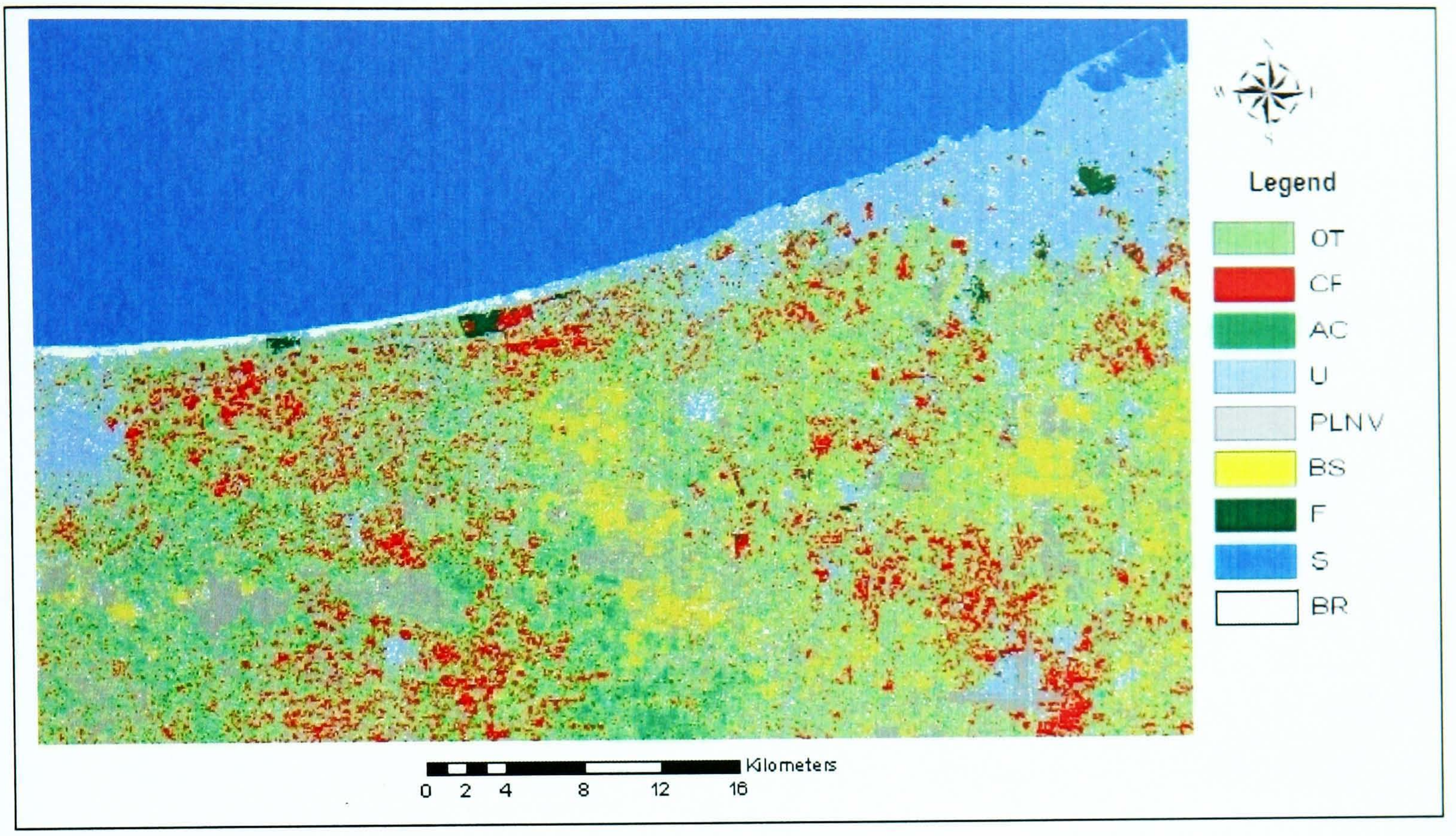

Figure 6.7. Land cover map produced by supervised classification of 1992 Landsat TM5 image.

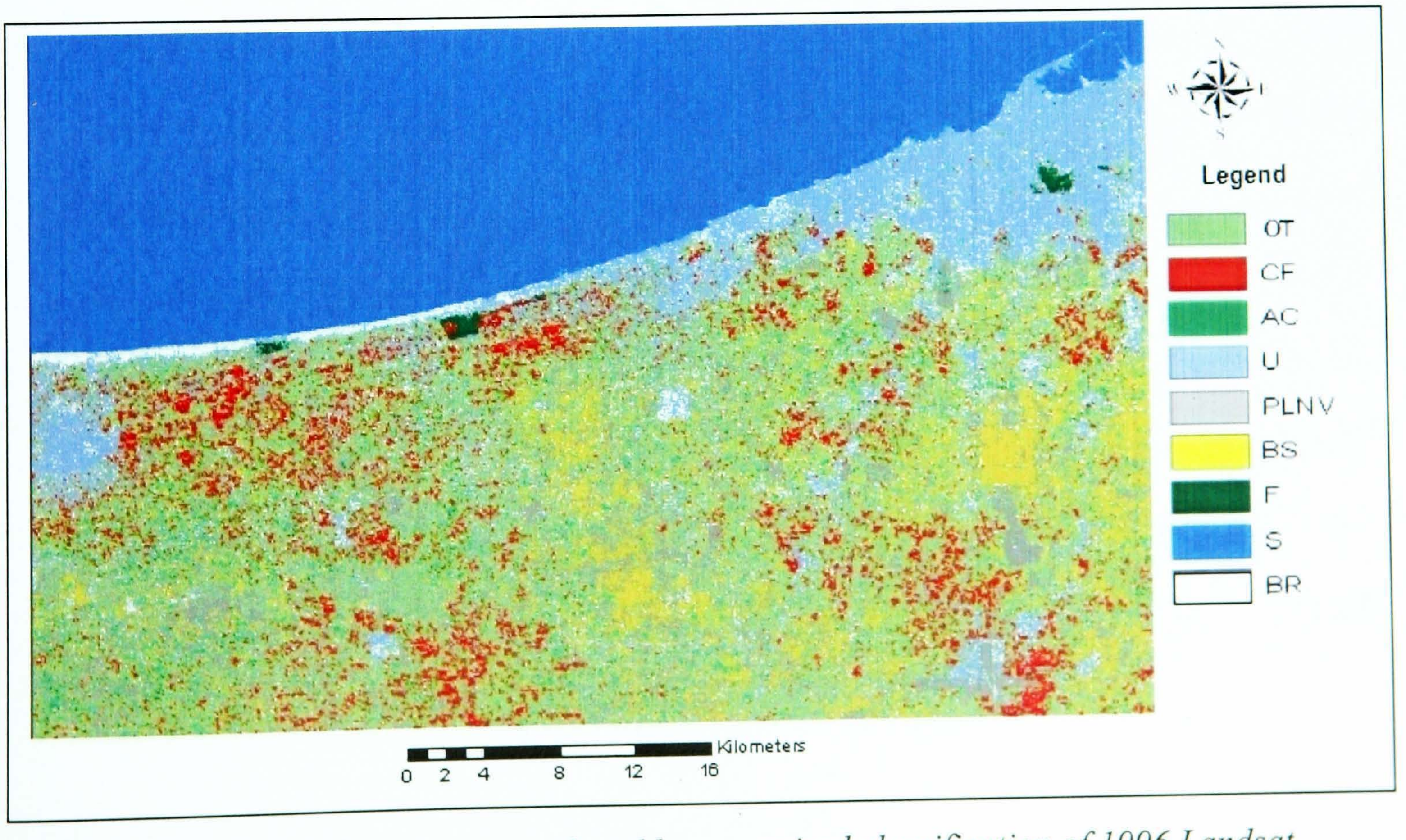

Figure 6.8. Land cover map produced by supervised classification of 1996 Landsat TM5 image.

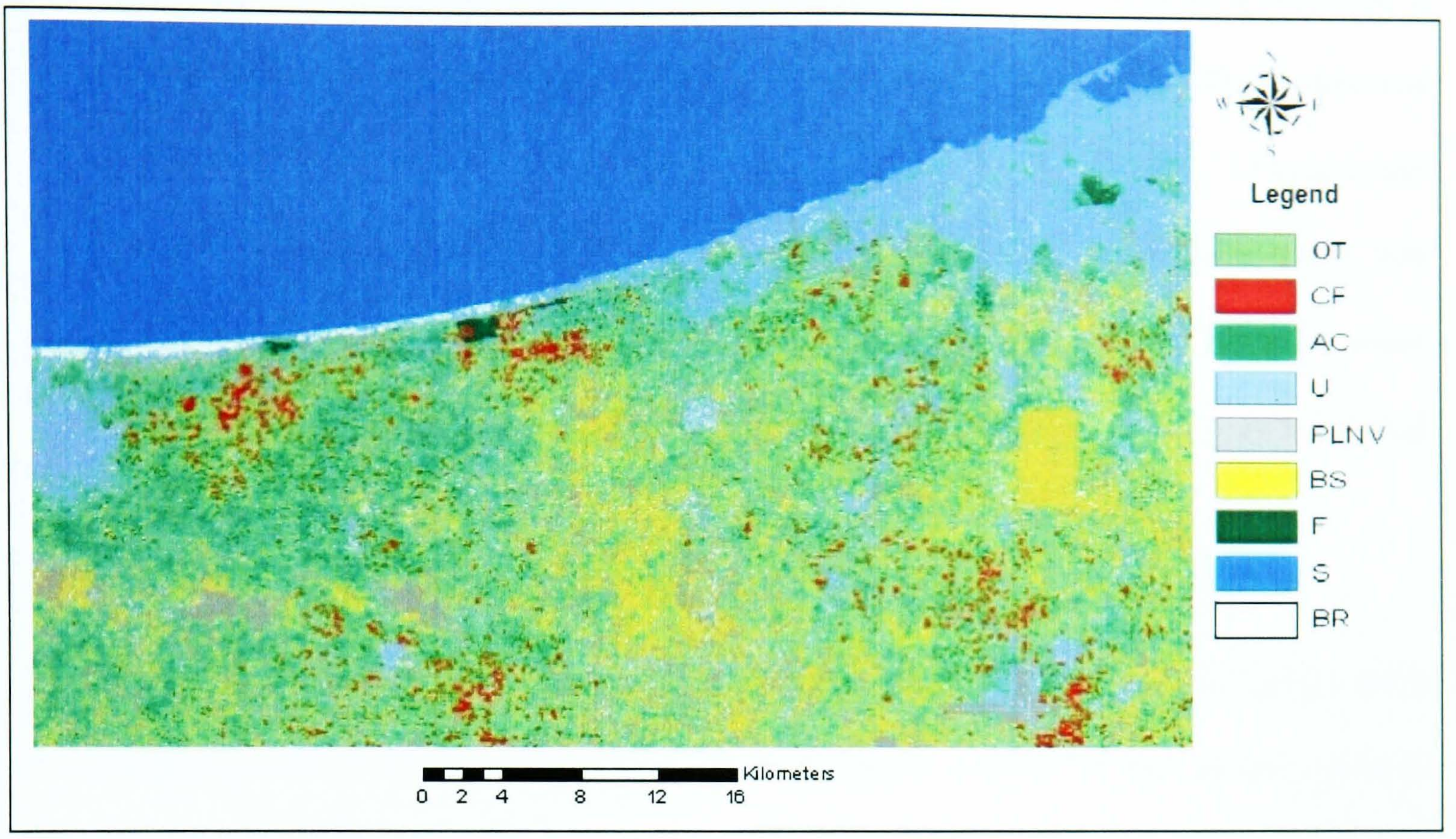

Figure 6.9. Land cover map produced by supervised classification of 2000 Landsat TM5 image.

6.3.1. Accuracy assessment

Accuracy assessment is a vital component in any study involving land cover classification (Boschetti *et al.*, 2004; Foody, 2002). The basic challenge is to quantify error caused by the spectral similarity of some classes and the complexity of boundaries between them (Powell *et al.*, 2004). In this case, the similarity between some classes, for example, OT, CF and AC classes, makes it difficult to find the boundaries when selecting the training samples especially in small areas (small fields). Therefore, the accuracy measures allow analysis of the sources of error and weaknesses of a particular classification strategy. However, there are other sources of error which might reduce the accuracy of the classification but these are less easy to quantify. Examples include mixed pixels and atmospheric reflectance effects (Foody, 2002).

Accuracy is usually based on an evaluation of the classified images in comparison to a reference dataset. The dissimilarities between the two datasets are typically interpreted as errors in the derived land cover map (Foody, 2002; Stehman, 1997). To assess and verify the accuracy of the classification results for each of the four images, about 900 points (pixels) from each image were selected randomly for comparison with the same pixel locations in either the high spatial resolution imagery (Quick Bird, SPOT 5 and SPOT XS) and/or from field data.

Firstly, to assess the classification of the 2000 Landsat TM5 image, the points were compared with the same points in a SPOT 5 image from 2002 and double-checked against the Quick Bird image from the same year. Although the high spatial resolution data are not exactly from the same date and/or time of the year as the Landsat TM data, the dates of data collection are close enough to assume that significant landscape change is unlikely to have taken place. Clearly, this analysis relied on a visual interpretation of the high spatial resolution datasets, but also included knowledge of the local area and from locations in the study area checked during the field trip.

To assess the accuracy of the 1996 Landsat TM5 image classification, the result was compared with the SPOT 5 image from 2002 which was the closest date available. In order to estimate the accuracy of the 1992 Landsat TM5 image classification, it was compared with the classified 1996 Landsat TM5 image and 2002 SPOT 5 image. Comparison with previously classified images was used to identify gross rather than detailed change in land cover, as the general pattern of land cover in many areas was not known to have changed. Finally, the 1987 SPOT XS image, with a spatial resolution of 20 m, was used to assess the accuracy of the classified 1988 Landsat TM5 image. In addition, points where land cover had not changed in all images were identified and also selected as reference points (Figure 6.10). These were also checked during the field visit (Appendix II-A).

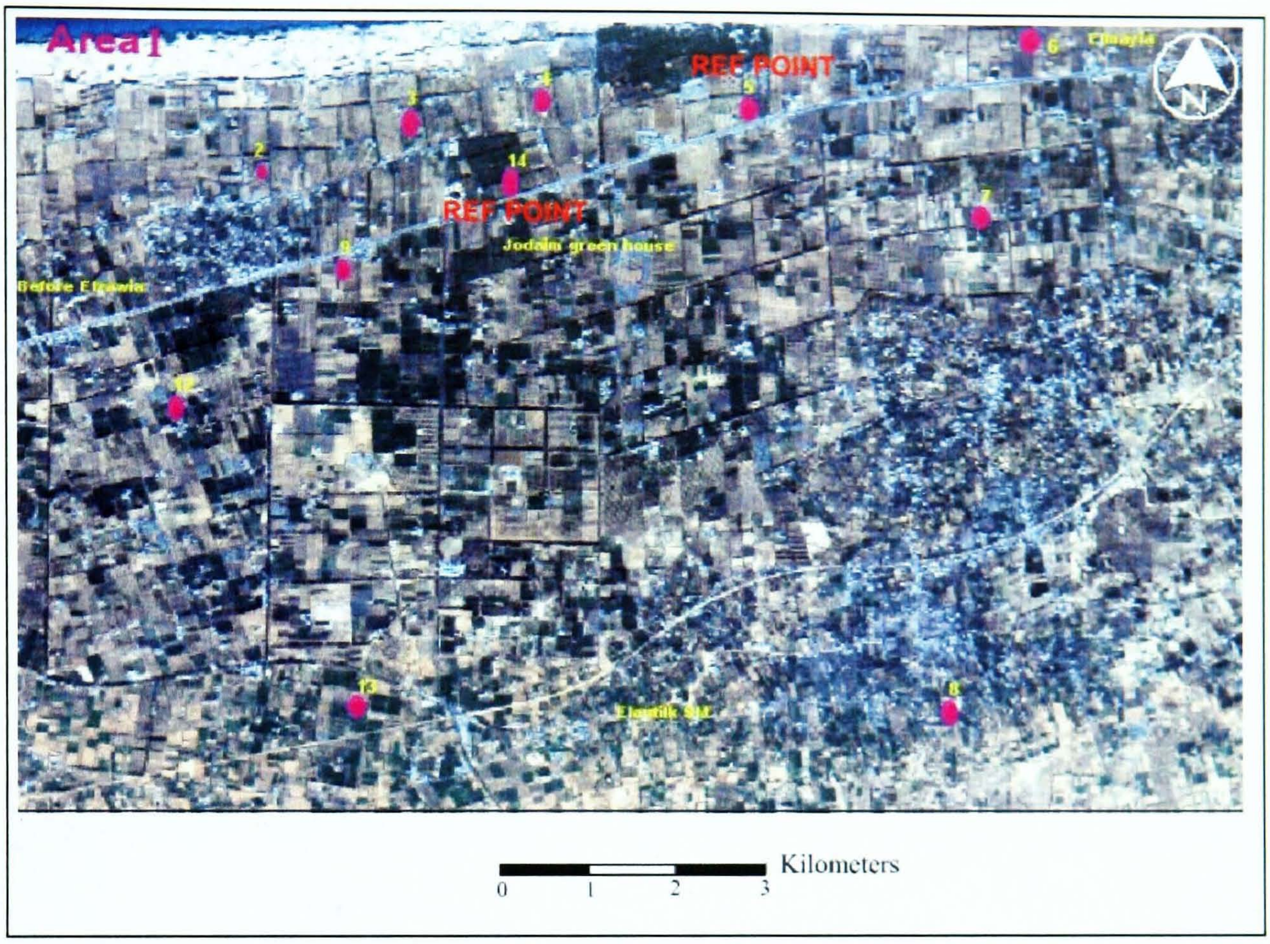

Figure 6.10. Example of check points in Area 1 including the reference points which have no change in land cover depicted in QuickBird 2002.

While it would have been preferable to have had independent land cover data for each date with which to assess the accuracy of the classified images, such information was not available and the above comparisons were deemed the closest (in terms of timeliness of data acquisition) and their use has considered to be a pragmatic solution on this occasion.

The correspondence between the classified image and the reference data/source can be assessed by a confusion matrix, which summarises the nature of the class allocations made by a classification (Foody, 2002). The confusion matrix (i.e. accuracy measure) for each classified image (Tables 6.3 to 6.6) illustrates the overlap and agreement between the classes (Yuan *et al.*, 2005).

Table 6.3. Confusion matrix for the 2000 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	126	1	59	2	31	7	0	0	0	56
CF	13	121	39	0	4	0	3	0	0	67
AC	37	8	149	1	4	5	1	0	0	73
U	0	0	0	19	3	1	0	0	0	83
PLNV	13	0	27	1	163	1	0	0	0	80
BS	0	0	0	0	1	20	0	0	0	95
F	0	1	1	0	0	0	12	0	0	86
S	0	0	0	0	0	0	0	22	0	100
BR	0	0	0	0	3	2	0	0	16	76
Producer's Accuracy %	67	92	54	83	78	56	75	100	100	

Table 6.4. Confusion matrix for the 1996 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	184	8	76	1	11	0	4	0	0	65
CF	24	176	44	0	0	0	3	0	0	71
AC	1	1	56	0	1	0	0	0	0	95
U	0	0	0	13	0	0	0	0	0	100
PLNV	13	1	9	0	174	1	2	0	0	87
BS	0	0	0	0	0	11	0	0	0	100
F	0	0	0	0	0	0	8	0	0	100
S	0	0	0	0	0	0	0	14	1	93
BR	0	0	0	0	0	0	0	0	9	100
Producer's Accuracy %	83	95	30	93	94	92	47	100	90	

Table 6.5. Confusion matrix for the 1992 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	155	7	80	0	9	0	5	0	0	61
CF	38	130	61	0	4	0	5	0	0	55
AC	0	1	65	0	0	0	0	0	0	98
U	0	0	0	17	1	3	0	0	0	81
PLNV	15	0	4	1	155	0	2	0	0	87
BS	1	0	0	1	0	47	0	0	0	96
F	1	0	0	0	1	0	6	0	0	75
S	0	0	0	0	0	0	0	26	0	100
BR	0	0	0	1	0	3	0	0	6	60
Producer's Accuracy %	74	94	31	85	91	89	33	100	100	

Table 6.6. Confusion matrix for the 1988 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	198	8	134	4	15	2	7	0	0	54
CF	22	153	57	1	0	0	3	0	0	65
AC	0	0	61	0	0	0	1	0	0	98
U	0	0	1	12	0	0	0	1	0	86
PLNV	16	2	12	1	147	1	1	0	0	82
BS	0	0	0	0	0	10	0	0	0	100
F	1	0	0	0	0	0	2	0	0	67
S	0	0	0	0	0	0	0	18	0	100
BR	0	0	0	6	0	3	0	2	13	54
Producer's Accuracy %	84	94	23	50	91	63	14	86	100	

An additional accuracy statistic is the Kappa coefficient that summarises the information provided by the confusion matrix (Bishop *et al.*, 1975, cited in Mather, 2004). Results from different classifiers applied to the same data set (e.g. ML and ANN) can be more easily compared in terms of accuracy using the Kappa value (Mather, 2004). Kappa values range from -1 to +1, with a value of zero indicating that chance agreement has an equal (uniform) effect on the classifier, a value of +1 indicating a perfectly effective classification with no contribution from chance agreement. Any negative values indicate a very poor classification. Montserud and Leamans (1992) recommended that a Kappa value of 0.75 or greater indicates a very good to excellent classification performance. The overall accuracy, producer's accuracy, user's accuracy and the Kappa statistic are summarized for all images in Table 6.7.

Table 6.7. Summary of user's, producer's and overall accuracy (%) and Kappa statistic value for each image classification.

Land cover Class	1988		1992		1996		2000	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
OT	54	84	61	74	65	83	56	67
CF	65	94	55	94	71	95	67	92
AC	98	23	98	31	95	30	73	54
U	86	50	81	85	100	93	83	83
PLNV	82	91	87	91	87	94	80	78
BS	100	63	96	89	100	92	95	56
F	67	14	75	33	100	47	86	75
S	100	86	100	100	93	100	100	100
BR	54	100	60	100	100	90	76	100
Overall accuracy %	67		71		76		71	
Kappa statistic	0.6		0.7		0.7		0.6	

The overall accuracies for 1988, 1992, 1996 and 2000 were, 67%, 71%, 76%, 71% respectively, with corresponding Kappa statistics of 0.6, 0.7, 0.7 and 0.6. A uniformly accepted classification accuracy of 70% is often mentioned in the remote sensing literature (Lillesand *et al.*, 2005) and in this case three of the four images met that criterion, whilst the Kappa values were good, rather than very good (Montserud and Leamans, 1992).

The confusion matrices show that the majority of confusion occurred among the vegetation classes OT, CF, AC and PLNV. User's accuracies for OT, CF and PLNV as individual classes were high, ranging from 67% to 95%, although the AC class had low user's accuracies ranging from 23% to 54%, the highest accuracy being for the 2000 image. This is to be expected given that those classes have already been identified as similar spectrally. Also, the spatial pattern of vegetation growth may give rise to spectral confusion. The spaces between the lines of trees, which can be sometimes 20 m or more (Figure 6.11), are often used to grow annual crops with the size of field between 1 to 10 hectares with different field pattern (e.g. squares and rectangles). In this way, farmers try to exploit the irrigated water as much as they can because of its scarcity.

Similarly, semi-natural vegetation might grow naturally between the trees. The effect of this will result in a variety of mixed pixels, particularly confusing the OT and AC classes. This practice has increased following a reduction in groundwater status and as a result the landscape has become more heterogeneous than before.

It is difficult to have complete confidence in the accuracy measures for the earlier images as the reference data are not contemporary. Also the accuracies are probably related to issues of training data selection, since it was more difficult to distinguish and select pure training areas in the earlier images because of a lack of independent reference data for training set selection. However, in general the resulting accuracy appears consistent with other studies that have attempted to classify land cover in semi-arid areas and so deemed acceptable for further analysis.

Figure 6.11 A farm in Area 1 showing the space between the lines of olive trees which are used to grow annual crops (photo taken on 5th July 2006).

6.4. Changes in land cover

The change in the extent of land cover classes in all images was clearly visible and occurred as either an increase or a decrease between successive dates (Figure 6.12, Table 6.8). Change in land cover classes was not uniform across all classes. For some classes, such as the OT class, the change between years was not always a decrease. For example, there was an overall increase between 1988 and 1992, then a decrease from 1992 onwards.

Table 6.8. Area (ha) of each land cover class in each image and the percentage of change from 1988 to 2000.

Class	**1988**	**1992**	**1996**	**2000**	**% Δ 1988-2000**
OT	39618	42413	40929	34771	-12
CF	13741	11123	9546	4865	-64
AC	7460	5651	3864	14908	99
U	10155	14789	14010	18699	84
PLNV	23503	17118	19186	12946	-45
BS	3248	8515	10719	14514	347
F	758	828	303	298	-61
S	45680	45872	45838	45931	0.51
BR	5505	3325	5237	2701	51

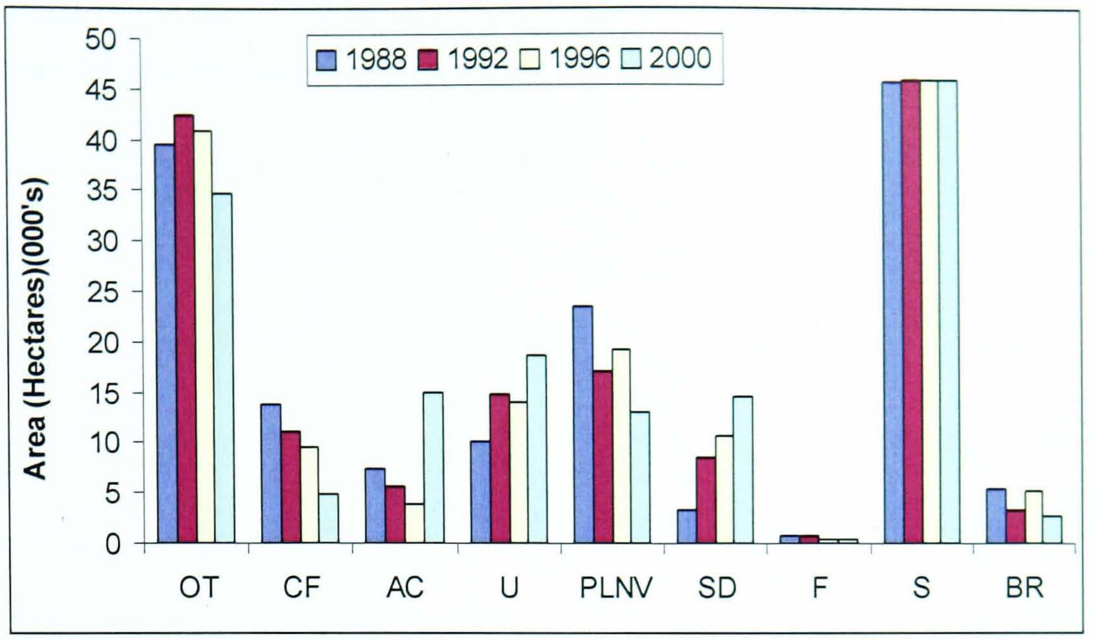

Figure 6.12. Extent of land cover classes (ha) from 1988 to 2000.

A clear decrease is observed in the area of the CF class (citrus fruit) over the time period as shown in Figure 6.13 and the negative change in the coastal area is higher than inland where the water quality has changed. The dominant fruit trees in the area are orange trees, which require a lot of water to grow and are therefore sensitive to groundwater change (both in terms of quantity and quality). Therefore, for this reason, most farmers have stopped growing them (see Section 5.2) and this pattern is observed clearly in the remotely sensed data.

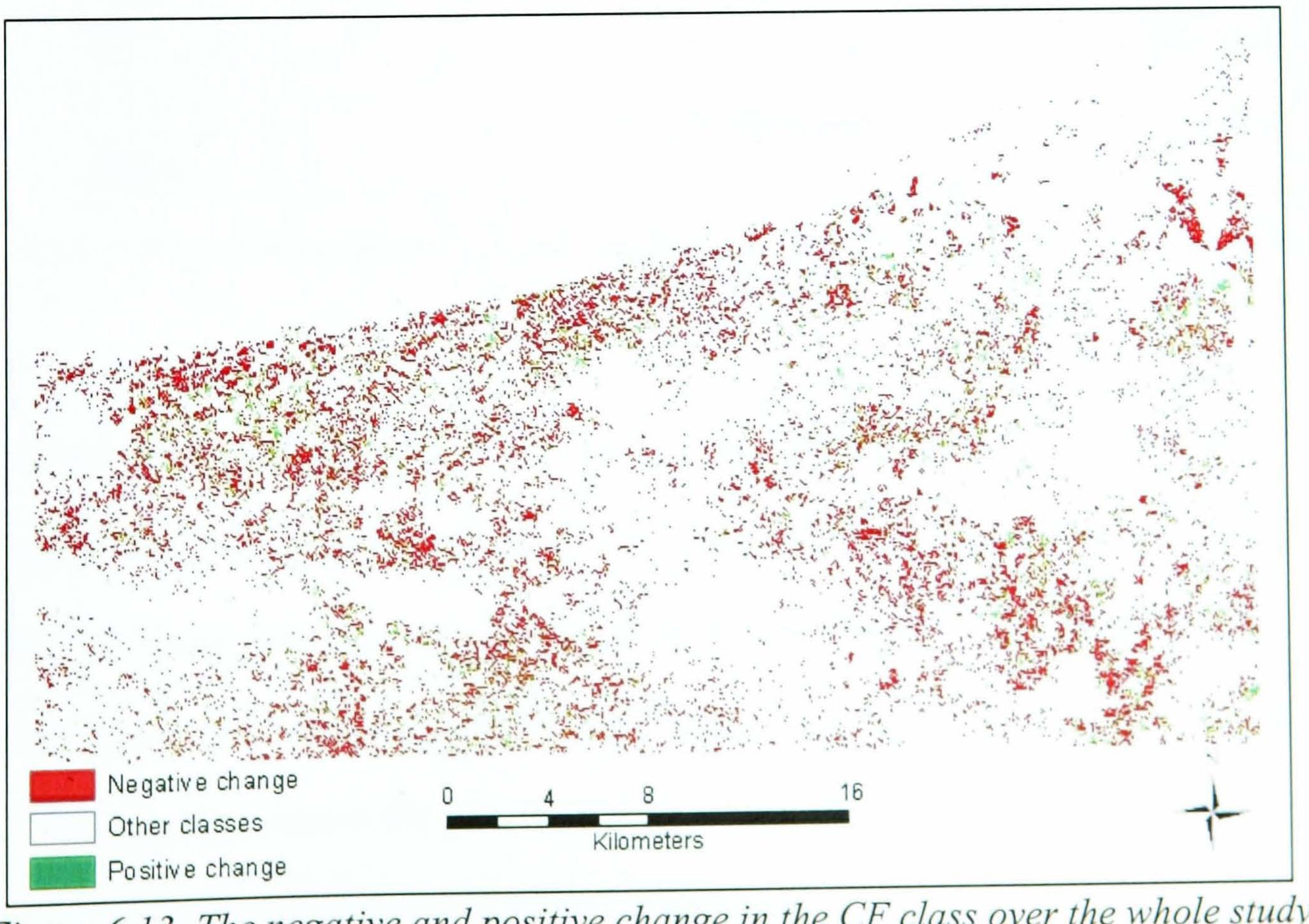

Figure 6.13. The negative and positive change in the CF class over the whole study area from 1988 to 2000.

Results from the questionnaire survey and informal comments from the farmers who reside in the region suggest that with both OT and CF classes there is now a greater utilisation of the space between the lines of trees for growing annual crops, as discussed previously. These results are confirmed by the change in the class extent observed from the classified images, which show that the AC class extent decreased from 1988 to 1992 and from 1992 to 1996, while it increased from 1996 to 2000 (Figure 6.14) after farmers decided to use the spaces between the lines of trees to maximise water efficiency (Table 6.8).

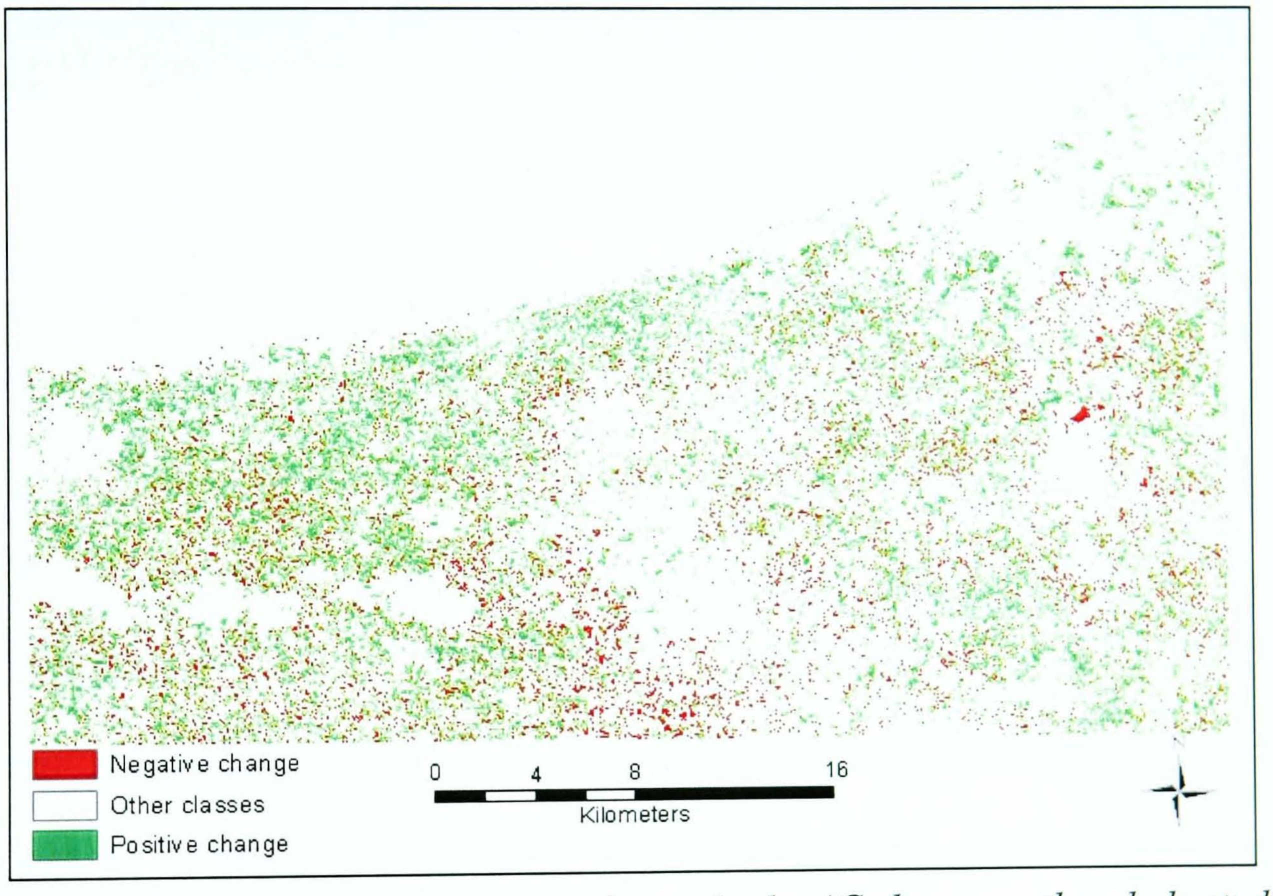

Figure 6.14. The negative and positive change in the AC class over the whole study area from 1988 to 2000.

Similarly, semi-natural vegetation (e.g. grasses and herbs) might be growing naturally between the lines of trees, particularly during the relatively wet months (September to May, see Table 6.9) or when the fields are irrigated and not ploughed for some time (Figure 6.15). In both cases, this might change the nature of the land cover visible, as well as creating issues for the extraction of training data either for classifying the images or to assess the accuracy of the classification.

Figure 6.15. Semi-natural vegetation (herbs) grown between the lines of orange trees, Farm C, 5th July 2006.

As groundwater is vital to support the growth of semi-natural vegetation in arid and semi-arid areas, any decline in groundwater might be expected to affect the semi-natural vegetation (Xu *et al.*, 2007; Munoz-Reinoso, 2001) which is largely located in the south of the study area. This supposed relationship, however, was not straightforward as the decrease observed in this class between 1988 and 1992 was reversed between 1992 and 1996, where a strong increase is seen. This is probably due to an increase in the total annual rainfall observed in 1995 and 1996, as recorded by the Azahra Meteorological Station (Table 6.9, Figure 6.16). This would lead to abundant vegetation growth for classes which are not usually irrigated and rely on depleted groundwater sources, i.e. semi-natural vegetation. The area of the class decreased again between 1996 and 2000, as rainfall returned to its sparse average figure and groundwater continued to become less available. Figure 6.17 shows the overall change in the period from 1988 to 2000 and the negative change in PLNV class is noticeable across the whole area.

Table 6.9. Monthly total of rainfall (mm) in the Jeffara Plain (Azahra Station).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
1988	51.0	6.0	7.0	0.0	0.0	0.0	0.0	0.0	18.0	//	20.0	160	**262.0**
1989	19.0	13.0	60.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	14.0	2.0	**118.0**
1990	10.0	//	12.0	5.0	5.0	0.0	0.0	0.0	10.0	0.0	51.0	12.0	**105.0**
1991	28.5	13.5	24.0	5.0	31.0	10.0	0.0	0.0	4.0	0.0	18.0	9.5	**143.5**
1992	3.5	25.0	21.5	3.0	2.5	0.0	0.0	0.0	0.0	4.0	15.5	7.0	**82.0**
1993	26.0	20.0	5.0	//	//	0.0	0.0	0.0	0.0	8.0	27.0	5.0	**91.0**
1994	19.0	4.0	3.0	25.0	5.0	0.0	0.0	0.0	0.0	10.0	2.0	21.5	**89.5**
1995	70.0	16.0	18.5	40.0	//	0.0	0.0	0.0	10.0	49.0	25.0	16.5	**245.0**
1996	14.0	55.0	35.0	8.0	//	0.0	0.0	0.0	8.5	//	36.0	7.0	**163.5**
1997	10.0	5.0	18.0	3.0	//	0.0	0.0	0.0	4.0	7.0	10.0	30.0	**87.0**
1998	25.0	16.2	17.0	//	//	0.0	0.0	0.0	//	//	12.0	9.0	**79.2**
1999	8.0	16.0	30.0	//	//	0.0	0.0	0.0	//	//	8.0	//	**62.0**
2000	//	25.0	8.0	//	//	0.0	0.0	0.0	//	9.0	//	//	**42.0**

Data source: Libyan Meteorological Department, Climatological Section.

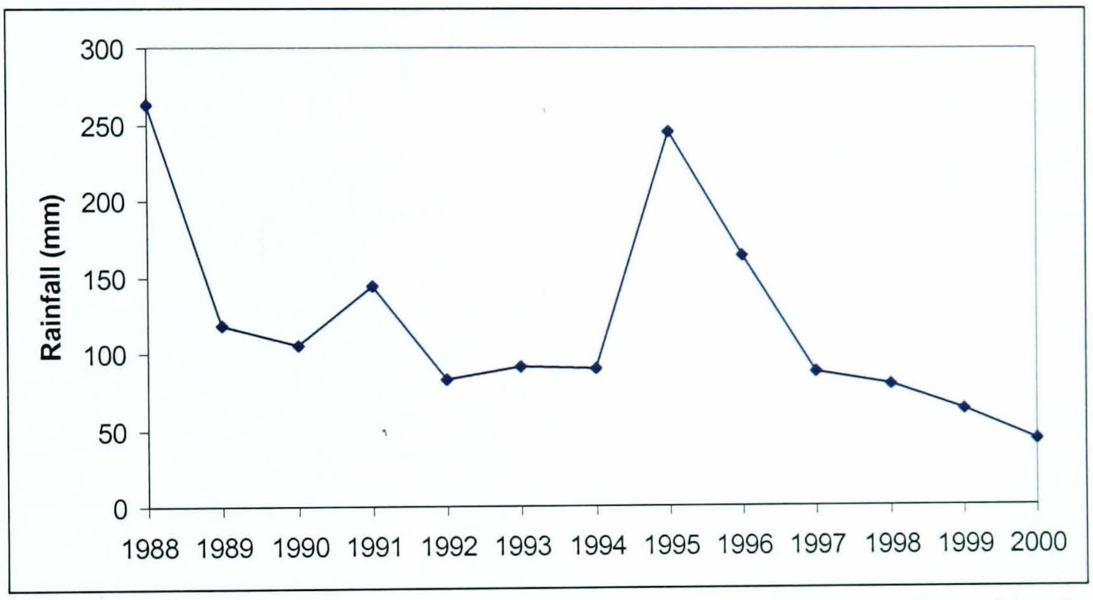

Figure 6.16. Change in total annual rainfall (mm) in the Jeffara Plain (Azahra Station) during the study period.

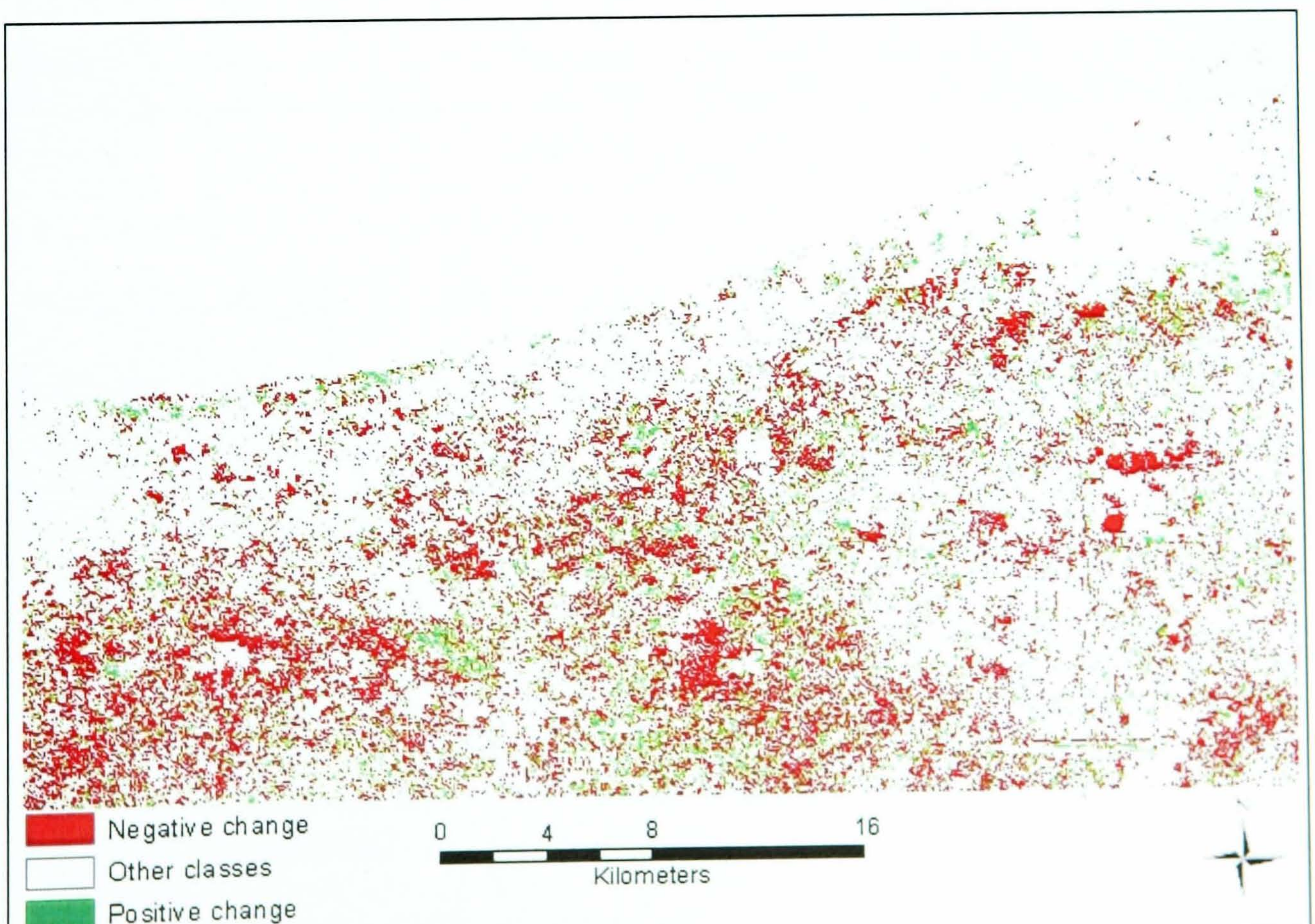

Figure 6.17. The negative and positive change in the PLNV class over the whole study area from 1988 to 2000.

The forest areas in the study region belong to the Libyan Government, who granted ownership of most of these areas to the people who work and manage the forest in the early 1990s. According to the questionnaire responses, it became apparent that most or all of these people chose to change the agricultural activities of the sites and tried to grow various different kinds of vegetation (in particular annual crops). Figure 6.18 illustrates that deforestation occurred between the years 1986 to 1993 around Tripoli city (Kredegh, 2002).

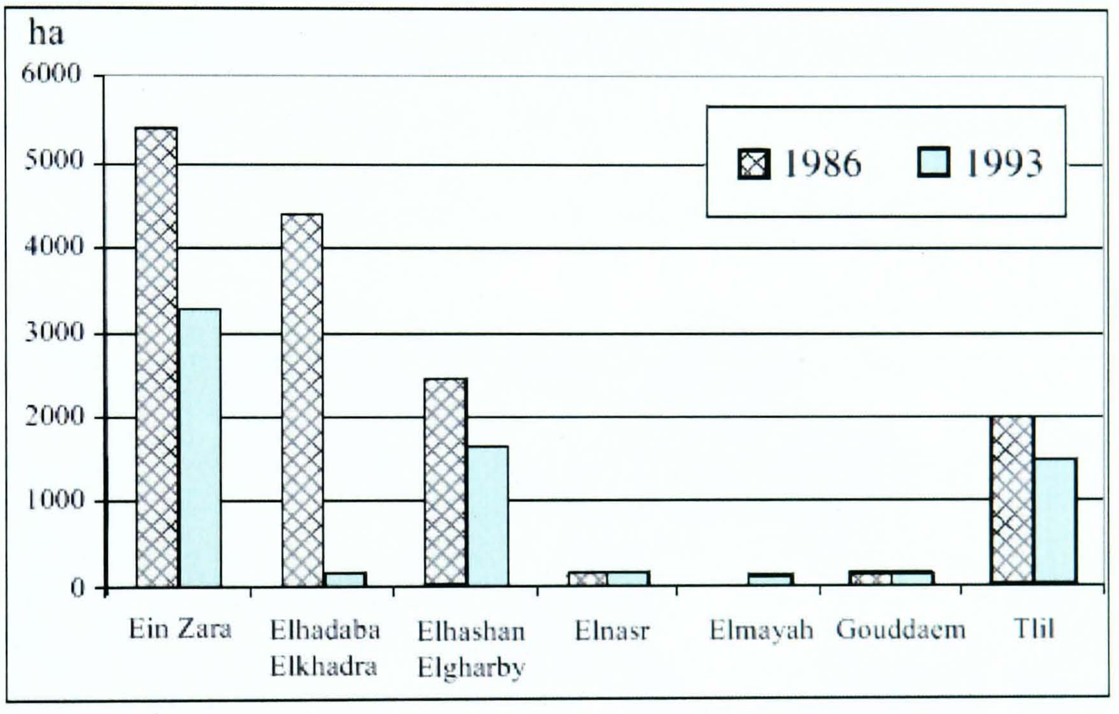

Figure 6.18. Forested area around Tripoli city, 1986-1993 (ha) (source: Kredegh, 2002) (Elhadaba Elkhadra, Elhashan Elgharby, Elnasr, Elmayah and Goudaem forest are in the study area).

The forest class decreased in the region from 1992 to 2000 (Table 6.8), a factor that is related to the change of the farmers, activities as mentioned in the previous paragraph. Figure 6.19 illustrates one of the farms in Elhashan Elgharby where the owners decided to remove the trees and grow other crops (informal interview), on the other hand the results of classification for the 1988 image over Elhashan Elgharby showed the forest area was 22.68 hectare (Figure 6.20 a and b) and then in 2000 the forest area is nil after the forest has been removed.

Figure 6.19. A site from Elhashan Elgharby which is located in Area 2, showing deforestation in the forest area; the arrows show the cultivated area which used to be forest (visited on 6th July 2006).

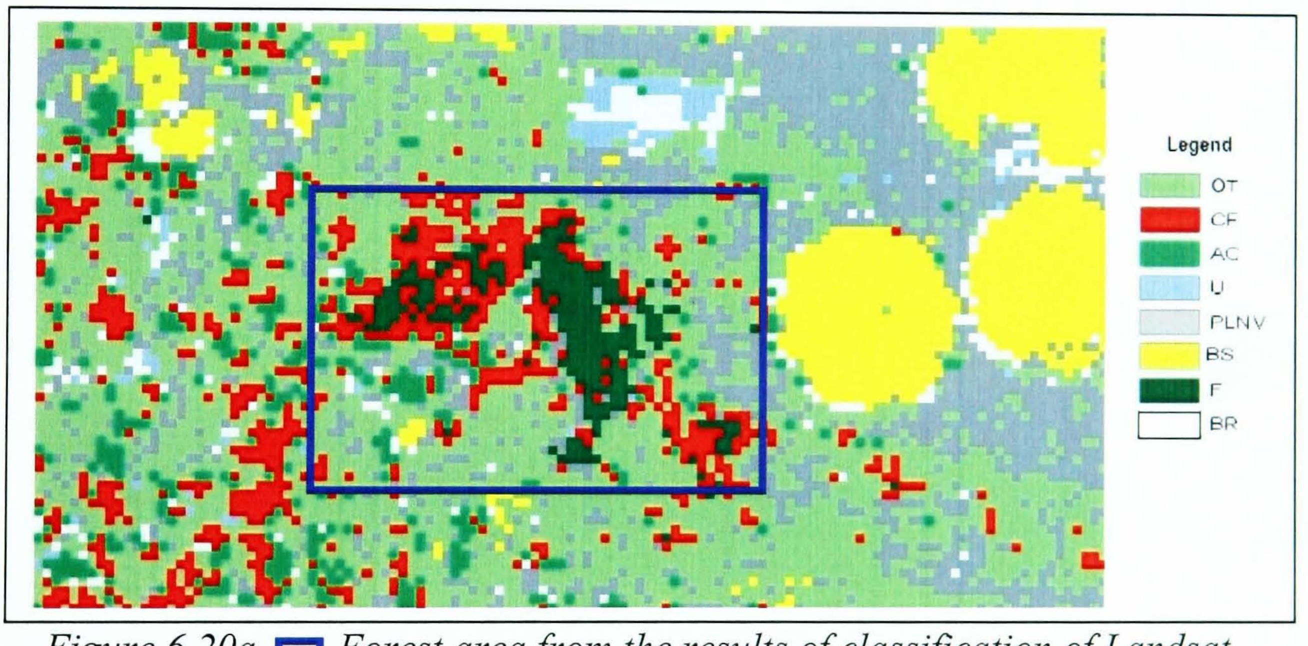

Figure 6.20a. ▭ *Forest area from the results of classification of Landsat TM5 from 1988.*

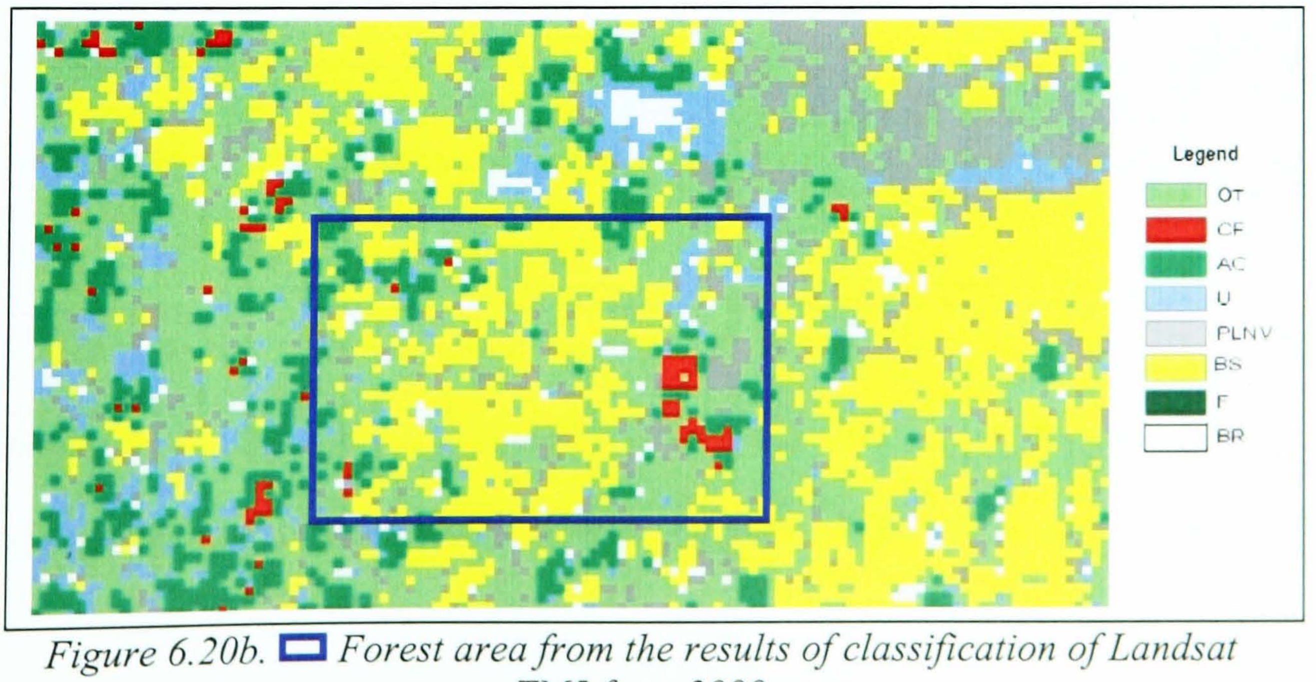

Figure 6.20b. ▭ *Forest area from the results of classification of Landsat TM5 from 2000.*

Vegetation classes OT, CF, PLNV and F have all decreased in their extent across the whole period. Figure 6.21 shows decreases of 12%, 64%, 44% and 60%, respectively over the study period from 1988 to 2000. By contrast, the AC class increased during the same period, as the farmers use areas between the tree lines. Additionally, when citrus trees have died due to water shortages, farmers have decided to remove these trees and these areas are now being used to grow different kinds of seasonal crops for a short period only (questionnaire and informal interviews), as these require less water to grow than orange trees.

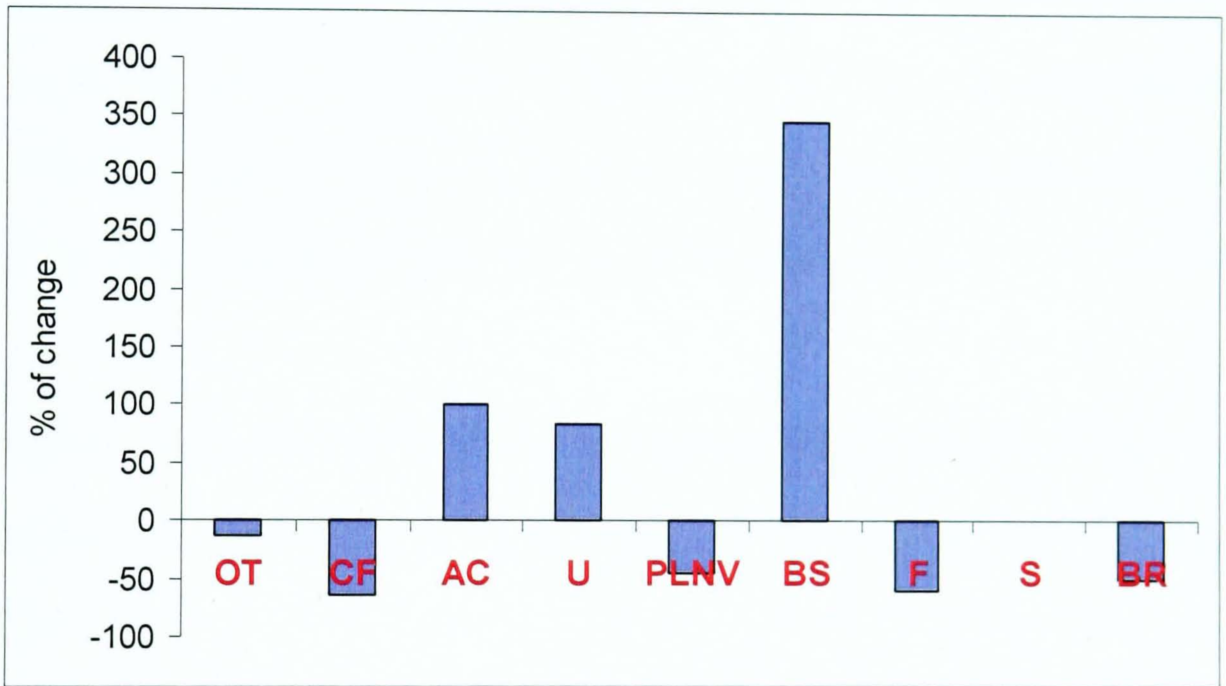

Figure 6.21. Percentage land cover change from 1988 to 2000.

The change in the urban class illustrates that urban areas are expanding every year, thus reducing the area available for agriculture. This concurs with many studies from this area that have shown that urban areas are expanding quickly and impacting upon available agricultural land (e.g. Vaughan and Oune, 1998). Additionally, there is some mis-classification between urban areas and the bare rock (BR) class. This is probably because both classes are composed of similar materials, i.e. rocks quarried from along the coast are used to build houses in the urban areas, thus leading to spectral similarity.

6.5. Analysis of local scale change

One of the major reasons for changes in many of the land cover vegetation classes is likely to be water availability. Given that in inland parts of the study area the problems of urbanisation and salination are negligible, it can be reasonably assumed that one of the major reasons for land cover change in the vegetation classes is groundwater availability, both directly (i.e. plants accessing groundwater directly, partially semi-natural vegetation) and indirectly as farmers alter their crops to cope with reduced availability of groundwater for irrigation. Since the main aim of this project is to find out what changes (if any) have occurred in the agricultural output resulting from groundwater depletion, several local study sites not influenced by urbanisation were selected in order to examine this in isolation. In addition, several specific sites along the coastal area were also analysed to look at the impact of salinization.

The study area was divided into five areas of interest (Figure 6.22) to compare the land cover changes at a larger scale, isolated from urban expansion and other industrial activities.

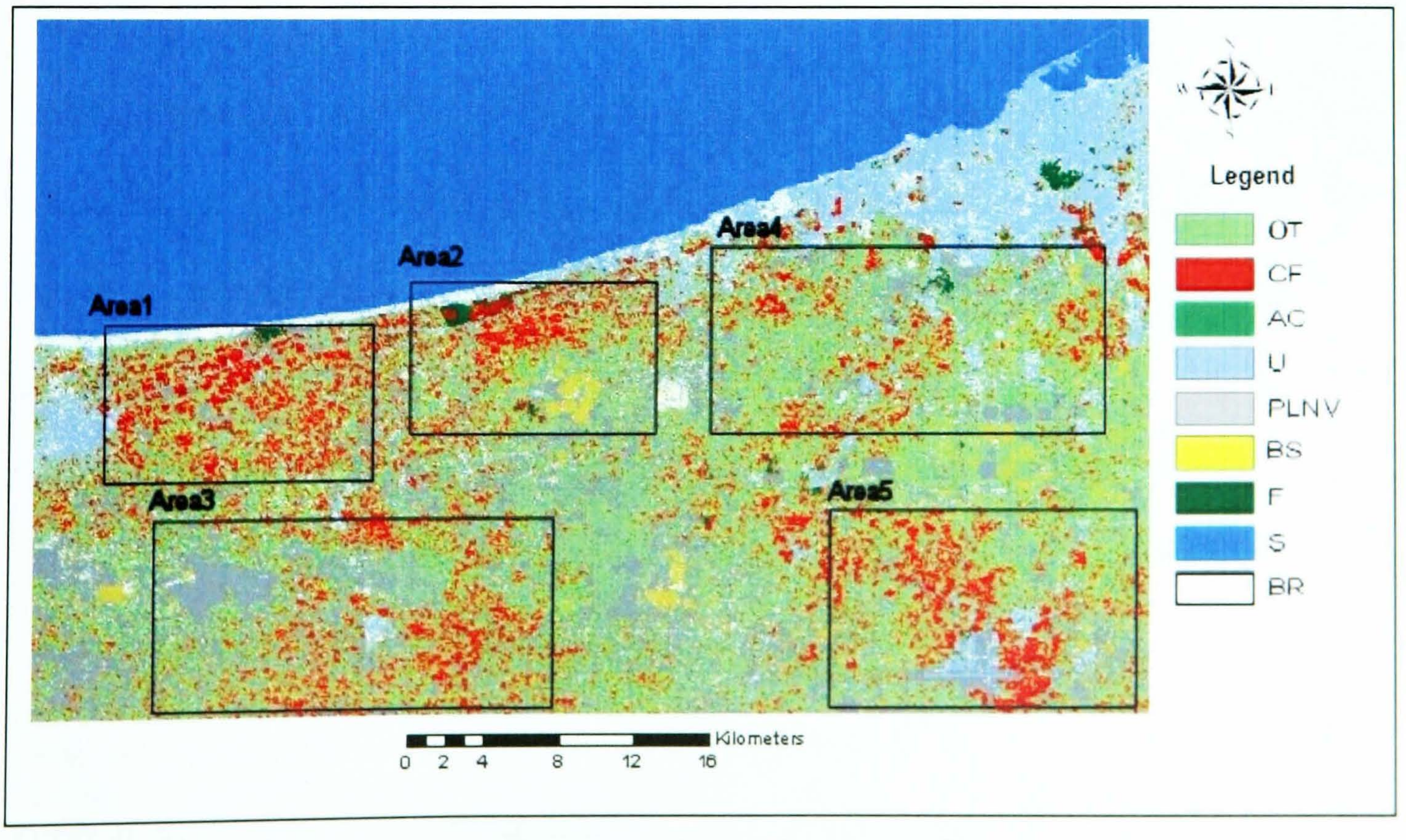

Figure 6.22. Location of specific areas of interest.

As shown in Figure 6.22, the selected areas cover most of the agricultural area within the Jeffara plain and, at the same time, they exemplify coastal and inland situations. The land cover change during the study period in each area is demonstrated in Figure 6.23 and Table 6.10. However, the similarity of these changes suggests that the cause is the same in all areas, which might be groundwater changes. The changes in land cover classes were similar in all areas but marginally different and the areas where the groundwater change in quantity and followed by quality changes are more affected Area 1, 3 and 5 (questionnaire survey). For example, the CF and PLNV classes have higher percentage of decrease in the coastal area compared with the inland areas.

Table 6.10. Changes (ha) in land cover in the five areas of interest from 1988 to 2000.

	Area1 (00-88)	**Area2 (00-88)**	**Area3 (00-88)**	**Area4 (00-88)**	**Area5 (00-88)**
OT	-230.22	-208.53	678.33	-1228	-382.77
CF	-1230.6	-767.61	-1420.2	-936.81	-1280.3
AC	1341.09	757.98	1015.02	980.91	847.17
U	653.58	616.32	649.8	1199.97	541.62
PLNV	-539.37	-543.06	-2063.6	-1490.7	-1039.7
BS	181.89	416.34	1333.53	1753.83	1439.37
F	-60.3	-76.95	-13.68	-55.89	-18.09
S	4.68	8.64	0	0	0
BR	-120.78	-202.05	-179.19	-215.46	-51.57

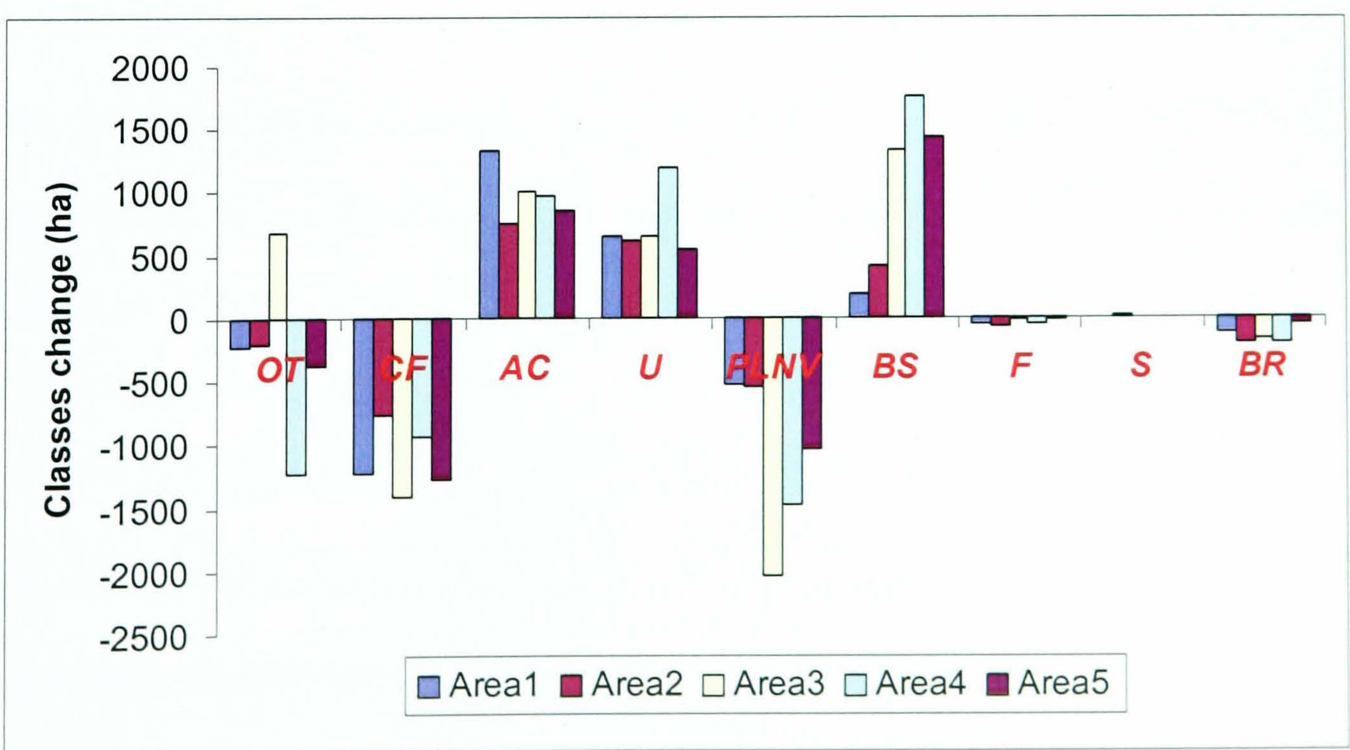

Figure 6.23. Change in land cover classes in the areas of interest from 1988 to 2000. Classes are OT= other trees, CF= citrus fruits, AC= annual crops, U= urban area, PLNV= pasture land with semi-natural vegetation, BS= bare soil, F=forest, BR= bare rocks.

To determine the nature of change at a more local scale (and of relevance to the questionnaire survey in particular) individual farms were selected and the nature of change noted (Figure 6.24).

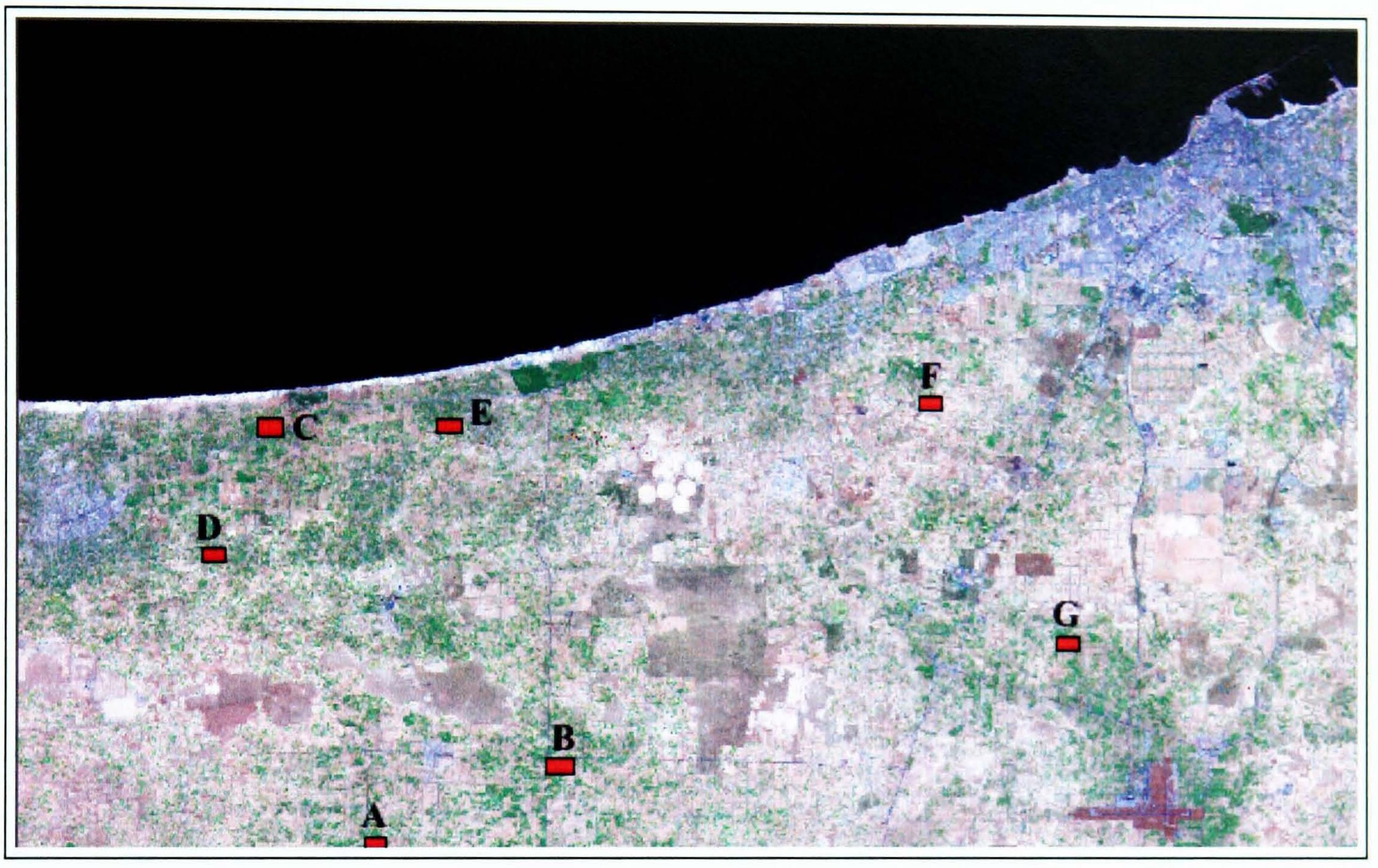

Figure 6.24. Individual farms in the study area which were used as farm scale examples of land cover change.

Farm A provided information on the change in the CF class and this was supported by evidence from the questionnaire survey and informal interviews during the field visit. In this case, the change in the areas devoted to the CF class within this farm was about 5 ha over 12 years (response from farm owner). The results from remote sensing data using the ML classifier (Table 6.11) show a similar decrease in the CF class during the study period from 1988 to 2000, as shown in the classified images (Figure 6.25a and 6.25b). A high spatial resolution SPOT 5 Image from 2002 (Figure 6.26) illustrates the state of the farm particularly the orange field which similar to the state of the field that was present in 2000, and show the shape of the orange filed (response from farm owner).

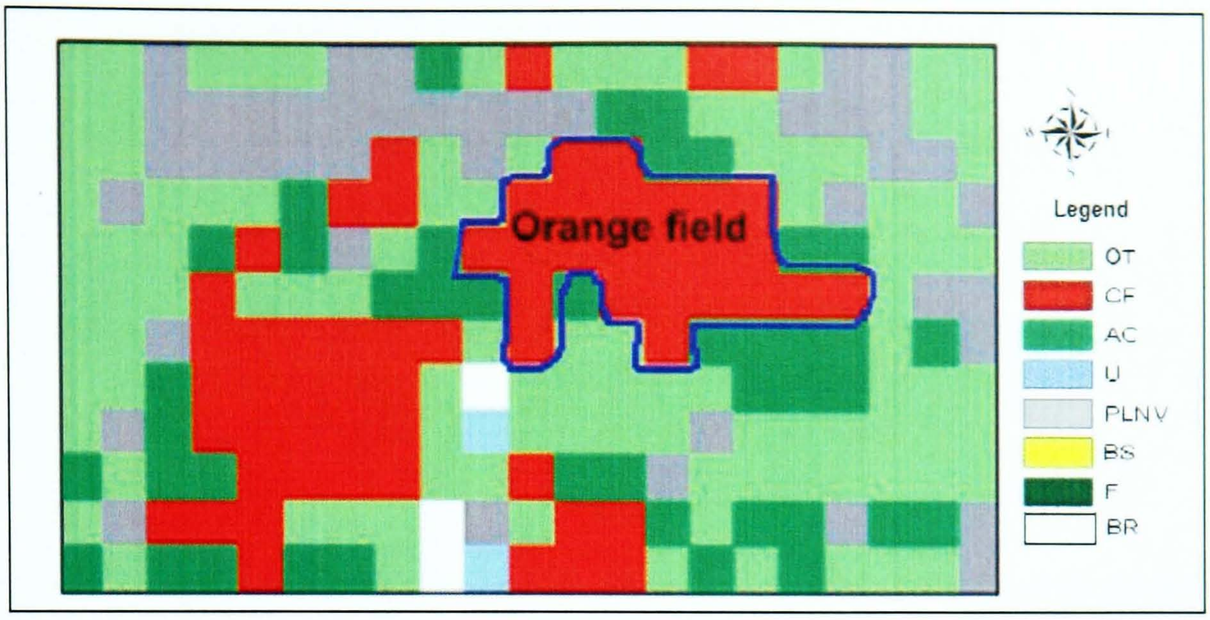

Figure 6.25a. Results of classification of Landsat TM5 from 1988 for Farm A.

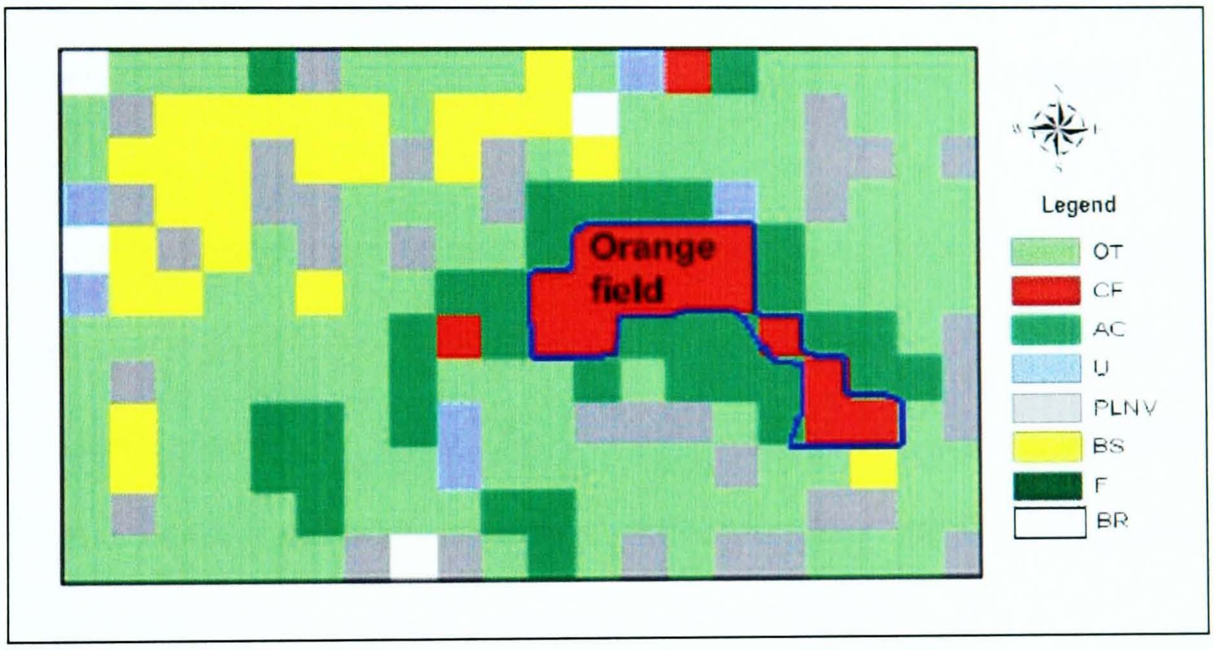

Figure 6.25b. Results of classification of Landsat TM5 from 2000 for Farm A .

Figure 6.26. Farm A covered by SPOT 5 image from 2002.

Table 6.11. Area (ha) for 1988 and 2000 images at Farm A.

Class	1988	2000
OT	9.09	10.98
CF	5.96	1.53
AC	3.78	3.15
U	0.18	0.99
PLNV	3.73	3.33
BS	0	2.34
BR	0.27	0.36

Figures 6.25b and 6.26 in particular are encouraging from an accuracy perspective as the shape and extent of the orange tree class appear very similar. A comparison between the two dates also highlights the large change in amount of land devoted to orange production at this farm, similar in magnitude to that described by the farmer.

As a second example, Farm B again illustrates the change in CF class over the study period. In this case, the CF class area has changed to the AC class (Figure 6.27a and 6.27b), a change confirmed when the area was compared with the high spatial resolution data (Figure 6.28). This occurred when the spaces between the rows of trees were used for growing annual crops when the orange trees died (Figure 6.29).

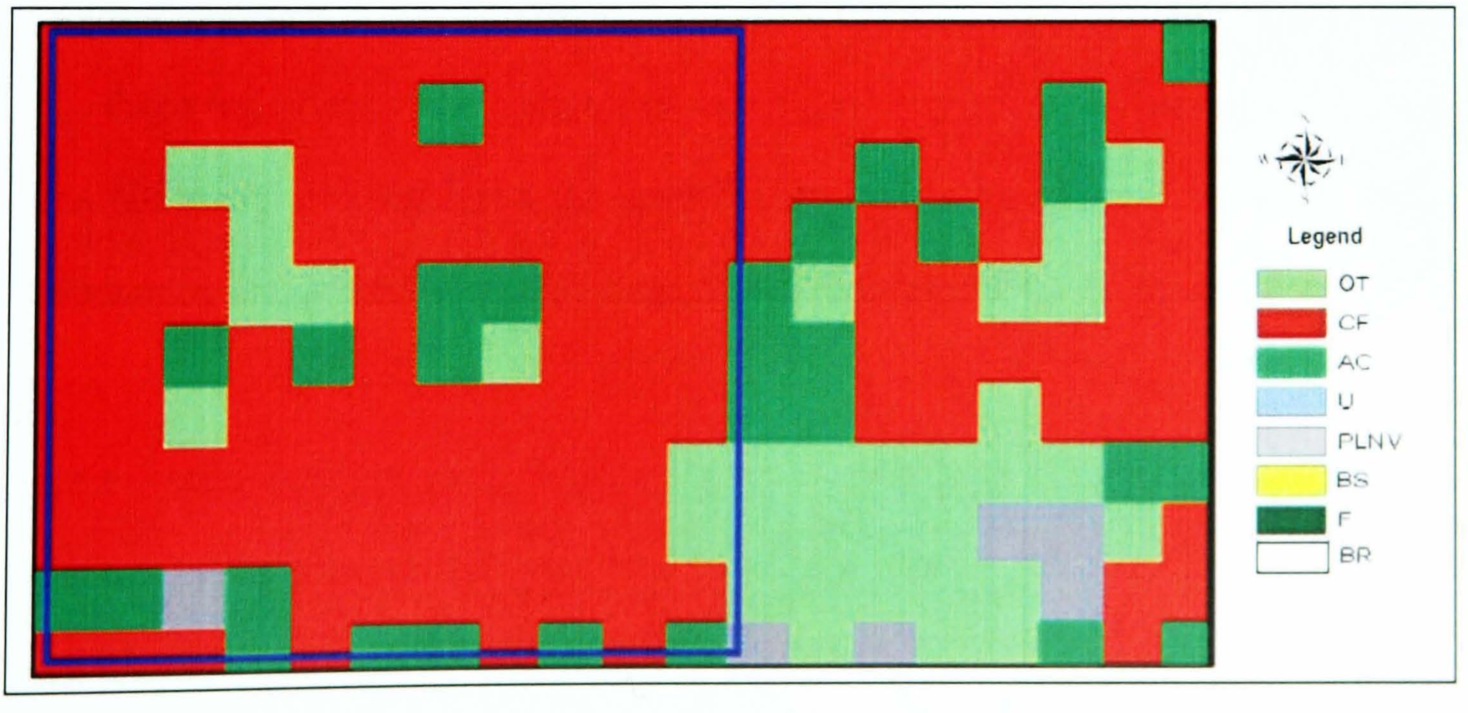

Figure 6.27a. Results of classification of Landsat TM5 from 1988 for Farm B.

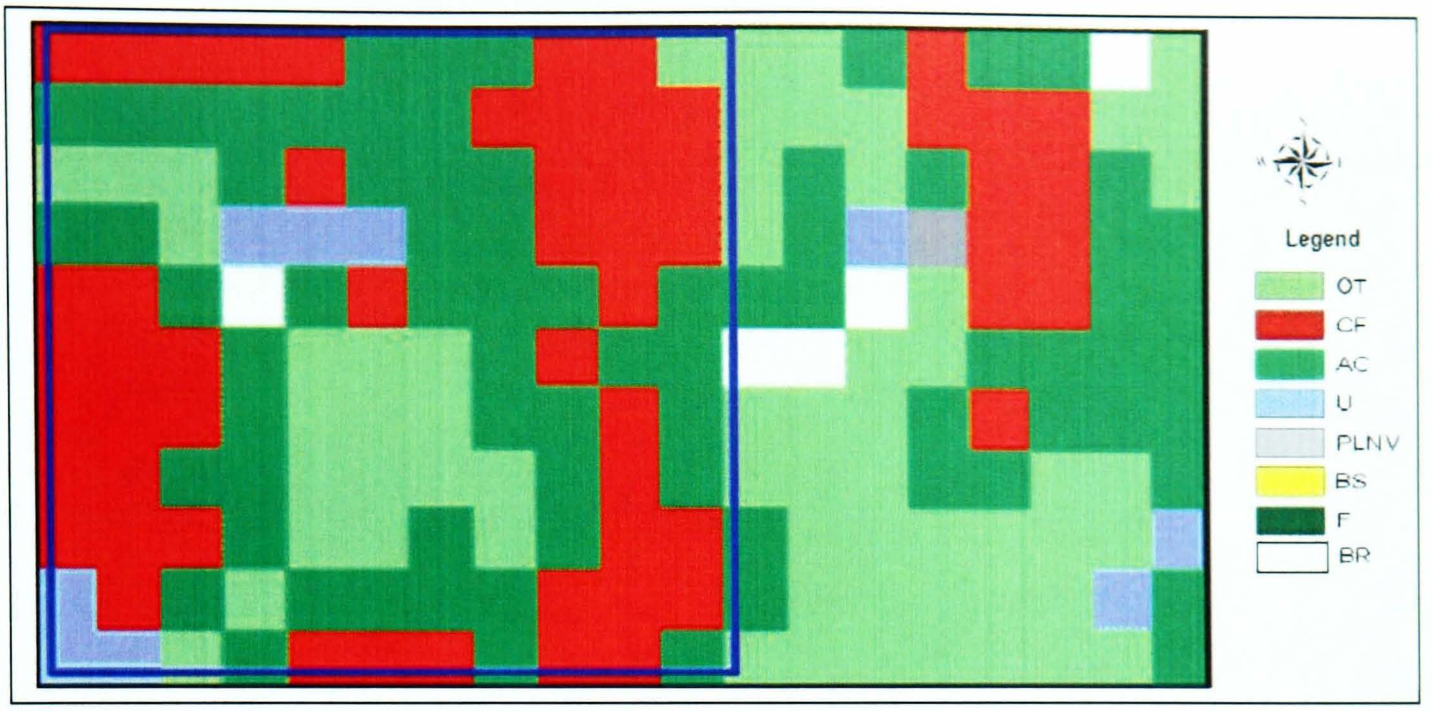

Figure 6.27b. Results of classification of Landsat TM5 from 2000 for Farm B.

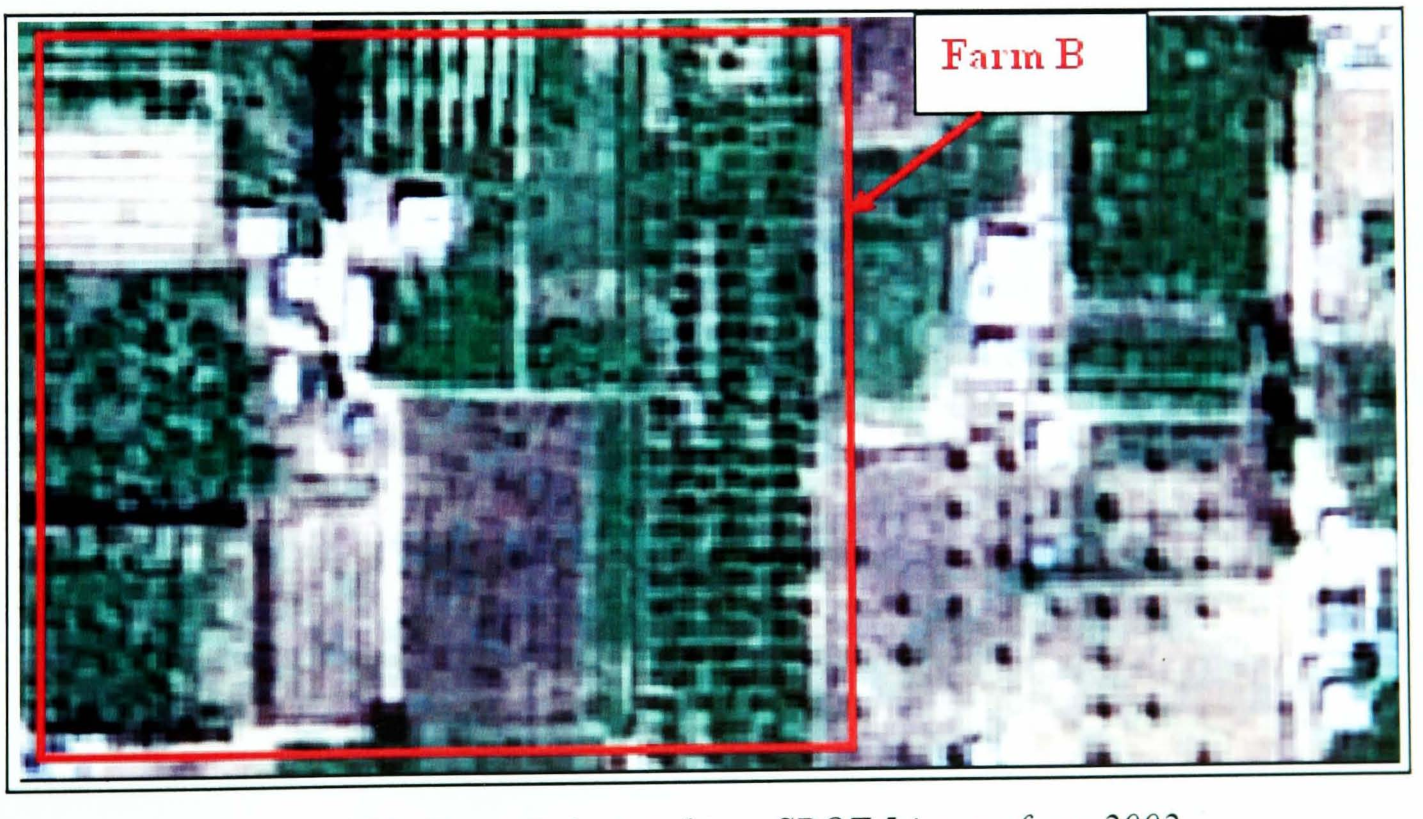

Figure 6.28. Farm B depicted in a SPOT 5 image from 2002.

Figure 6.29. A photograph of the orange field in Farm B where the space between the rows is now used to grow annual crops (8th July 2006).

The farm scale analysis confirms the changes in the land cover and that the results were realistic and comparable with the field observations and the questionnaire responses.

6.6. Summary

The results of the analysis described in this chapter demonstrate that ML supervised classification of Landsat TM5 imagery can be used to produce reasonably accurate maps of land cover change either for the whole area or at an individual farm scale. The purpose of the classification was to identify changes in land cover, and in particular vegetation classes that might be linked to groundwater changes in the study area. The classes OT, CF, AC and PLNV were identified as those most likely to be related.

The changes observed show a marked decrease in the extent of the citrus fruit class, as well as other decreases in the OT and semi-natural vegetation classes. From the questionnaire responses and fieldwork presented in Chapter 5, it is clear that these have been both directly and indirectly affected by groundwater availability. The one class that did increase in extent was the AC class, which results from farmers adopting a different growing strategy and maximising water efficiency by growing these high yield, short term crops in the spaces between the remaining trees. This has led to a more heterogeneous landscape which may have had a detrimental effect on the selection of training data and pixels for assessing the accuracy of classification images.

The results suggest that ML can be used to map land cover in the Jeffara Plain, but errors persist and overall accuracies are not necessarily as high as they could be, e.g. Kappa accuracies described as 'good' rather than 'excellent'. Hence there is a need to investigate an alternative image classification method to either improve or at least validate the patterns in land cover observed. Many researchers have reported that an ANN classifier can classify images with higher accuracy than ML classifier, and this was, therefore, investigated further in Chapter 7.

CHAPTER SEVEN

Landcover change characterisation using a neural network approach

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7.1. Introduction

The use of Artificial Neural Networks (ANNs) for mapping land cover is becoming much more common (e.g. Aitkenhead and Wright, 2004; Atkinson *et al.*, 1997; Foody *et al.*, 1997; Jarvis and Stuart, 1996; Mendoza *et al.*, 2004; Pal and Mather, 2003; Tatem *et al.*, 2002). Specifically, several studies have compared image classification results from ANNs against statistical parametric techniques (e.g. Maximum Likelihood), with most reporting that using an ANN classifier results in considerably higher accuracies (Berberoglu *et al.*, 2000; Chiuderi 1999; Foody *et al.*, 1992; Kavzoglu and Mather, 1999), although classification accuracy may not be the only criteria by which a technique is judged a success. In addition, ANNs have been applied to classify Landsat TM data to map vegetation changes specifically and have provided realistic results (Carpenter *et al.*, 1999; Foody *et al.* 2003; Han *et al.*, 2003; Ritter and Hepner, 1990; Tatem *et al.*, 2002).

The results from the ML classification in Chapter 6 show the broad changes in land cover patterns with comparative results to subjective analysis of the high spatial resolution data, questionnaire survey and field work. However, there are some specific classes of interest where there is significant confusion and uncertainty, such as the OT and CF classes with the AC class, which may lead to an incorrect assessment of the role of groundwater driving land cover change. This confusion may be due to many reasons, including mixed pixels (Foody *et al.*, 1997) and noisy data (caused, for example, by ineffective atmospheric correction). The ability of ANNs to deal with mixed pixels and noisy data is well documented (e.g. Benediktsson *et al.*, 1990; Jarvis and Stuart, 1996). Also there are other advantages including the fact that no statistical assumptions are made about the data (Mather, 2004).

As an attempt to provide an independent (in terms of methodology) approach to map the land cover of the Jeffara Plain, and address the issue of class confusion and overlap, an opportunity to implement an ANN approach arose and this was used to classify the same remotely sensed data used in Chapter 6. This also provides an opportunity to compare the performance of a statistical (ML) approach with a non-parametric ANN approach to classify multi-date imagery. This chapter provides a description of the methodology, results observed and a comparison of the two sets of results.

The network was trained using data derived from training sets across the image, following which an independent validation data set was used to test the trained network, before the network was applied to the whole image. Each image was classified separately and then the land cover patterns were compared as before.

7.2. ANN training

The collection of training data is an important stage for the classification process and the resulting classification accuracy (Campbell, 1981; Foody, 1999; Hixon *et al.*, 1980; Mather, 2004). Training data should be acquired with consideration to the generalization ability of ANNs. The most useful training samples for classification with a multilayer perceptron neural network are those which lie on the edge of the class distributions in feature space and between the distributions of two or more classes (Foody, 1999). Artificial Neural Networks require large amounts of training data to both train the network and then validate the training, i.e. to ensure the network is adequately trained (see Section 2.5.2). This is in addition to including pixels required to test the accuracy of the resulting classification.

To test the importance of training set definition, two independent data training sets were extracted from the image data. The first contained individual pure pixels, selected from fieldwork and analysis of the high spatial resolution image data. The second training set comprised exactly the same pixels used to train the ML classifier in Chapter 6, derived from regions rather than individual pixels (i.e. sets of individual pixels defined within a polygon rather than pixels extracted in isolation). The first training set contained 200 pure individually located pixels for each class. Half of the training set was used to train the network, and the rest used to validate the trained network (testing data).

The second training data set used pixels from the same polygons (AOIs) defined to select training samples for the ML classifier. These training areas included pixels of 'mixed origin' rather than selected individual pure pixels, and therefore would possibly include more inter-class variance in reflectance. The number of pixels in the second training data set was not the same as the first training data set. Training sets (AOIs) for each class were converted into an ASCII file and then randomly divided into two groups, with one group used as training data pixels and the other group as testing (validation) pixels.

7.3. ANN design and generation

The most commonly used neural network model for image classification in remote sensing is the multi-layer perceptron (MLP) trained by the back-propagation algorithm (e.g. Atkinson *et al.,* 1997; Lee *et al.*, 1990; Lippmann, 1989; Ye *et al.*, 2006; McClelland *et al.,* 1989). A back-propagation neural network was used to classify the land cover in each image of the study area, using software written by Dr Matthew Aitkenhead (University of Aberdeen), within the Microsoft Visual Basic 6.0 environment. The images were classified into the same land cover classes used in the ML classification (Table 6.2), with each class allocated to a specific output node of the network. The input layer included the six spectral bands from the Landsat imagery, and 12 image texture measurements derived from the Grey Level Co-occurrence Matrix (GLCM). GLCM is a common method of obtaining textural information from imagery, which makes use of the different mixture of pixel brightness values (grey levels) that occurs in an image. Such textural information (including pixel contrast, dissimilarity and homogeneity) has been shown to help improve the effectiveness of mapping land cover with an ANN (Aitkenhead *at el.,* 2008).

The architecture of artificial neural networks is determined by available inputs and the desired number of output classes. Other elements, such as the number of hidden nodes, learning and training parameters, are often determined through trial and error, or rules of thumb. For example, Kolmogorov's theorem suggests that the number of hidden nodes should be $2n+1$, where n is the number of input units in the network (Atkinson *et al.,* 1997), but in reality this rarely results in the optimum design (Kavzoglu and Mather, 2003). The ANN, therefore, had 18 input nodes, and nine output nodes (classes). One hidden layer was used, with a total of 40 nodes (Figure 7.1). This layer size was obtained using trial and error, with improvement in mapping accuracy up to this point and none with larger numbers of hidden nodes (Kanellopolos and Wilkinson, 1997).

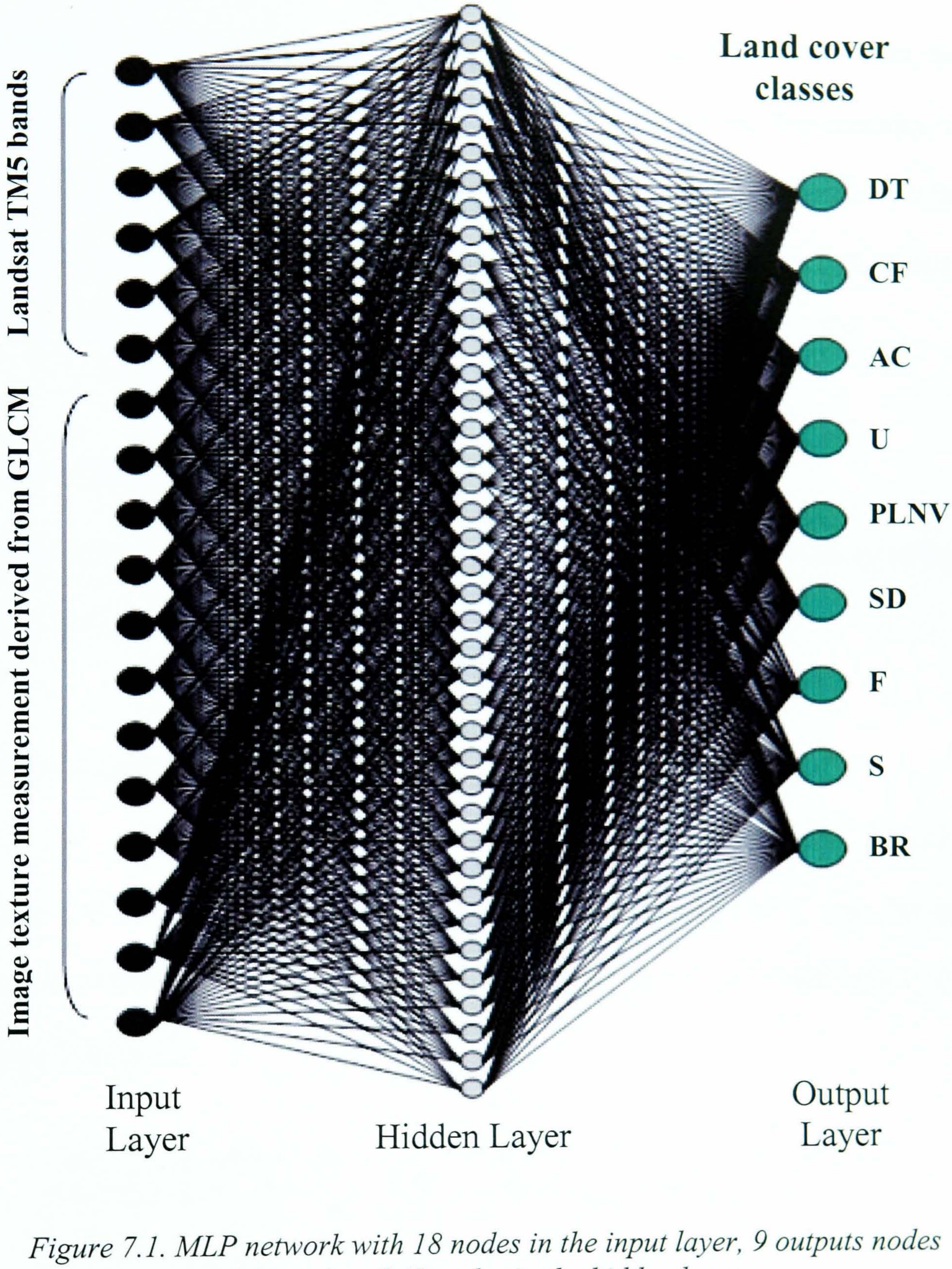

Figure 7.1. MLP network with 18 nodes in the input layer, 9 outputs nodes (classes) and 40 nodes in the hidden layer.

The training rate for connection weight adjustment was set to 0.1, with a momentum value of one for each node. These values were also obtained using trial and error. Training was carried out by training a separate neural network for each year. It was found that if a single network was trained using training data from all four images, the overall accuracy was slightly reduced, by approximately 1%. As the individual network accuracy rates were approaching or exceeding 90%, it was felt that even this small decrease in accuracy should be eliminated. The total number of training steps used to train each network was 200,000. Testing was carried out using independent data that had not been used to train the neural networks. For practical reasons, the operation of the ANN was conducted by Dr Matthew Aitkenhead (University of Aberdeen), who ran the training data through the software that he had written. However, all the definition of training data, analysis and interpretation of results was completed by the author.

7.4. ANN Classification Results

Two different classification results were derived from the ANN classifiers, produced from each of the two independent training datasets.

7.4.1. ANN trained with individual pixels

The ANN was first trained with individual pure pixels. However, the resulting classification (Table 7.1) was not realistic in terms of the pattern of land cover change observed in the high spatial resolution validation data, previous ML classification, and questionnaire responses.

Table 7.1. Estimated area (ha) of each land cover classes derived from an ANN classification using individual pixel training data.

Class	1988	1992	1996	2000
OT	27857	34111	41672	43300
CF	8979	8323	9293	9366
AC	13048	17204	16283	7085
U	13665	12384	10636	13526
PLNV	13902	8870	7832	16847
BS	22702.4	20626.7	16010.7	11592
F	934	1001	910	1150
S	45801	45915	45786	45989
BR	2640	1069	1198	876

The results show that between 1988 and 2000 the classes OT and CF increased in areal extent, while the AC class decreased. This is at odds with the analysis in Chapter 7 and observations in Chapter 6. In addition, the classification shows a decrease in the urban class, which again is unrealistic given what is known about the urban expansion in the region (Vaughan, and Oune, 1998). These errors in classification are most probably due to the poor definition of the classes, in terms of characterizing the within class pixel reflectance distribution. For example, Table 7.2 illustrates the statistical results of both training datasets collected as individual pixels and regions (AOIs) for both classes OT and CF.

Table 7.2. Statistical descriptions of OT and CF class datasets.

Class	Method	No of samples	Band	Mean	Standard deviation
OT	Pure pixel	20 pixels	1	20.7	23
			2	20	22
			3	38.44	43
			4	51	56
			5	112.7	119
			7	59	64
	(AOI)	15-20 pixels	1	24	4.9
			2	24	5
			3	45.5	8
			4	58.5	8.7
			5	123	15.7
			7	66	11
CF	Pure pixel	20 pixels	1	10	13.22
			2	11	13.5
			3	16	18
			4	55	60.5
			5	63	70
			7	25.4	30
	(AOI)	15-20 pixels	1	11	2.3
			2	12	2
			3	18.6	4.4
			4	54.8	5
			5	67.3	11
			7	29.3	7

There is a clear difference between the statistical results of the two methods of training data collection. The mean for the pure pixel method is smaller compared with the polygon method. Also the standard deviation is higher in the pure pixel method than the polygon method. The high standard deviation as shown in Table 7.2 might suggest that there are one or two 'pure' pixels that have been mis-identified but included in the training data. However, this indicated that one or two incorrectly included pixels have a much larger influence on the training data from individual pixels than the training data defined by polygons. Consequently, training data size is probably the issue (Foody, 1999). This may be due to class heterogeneity and/or the intrinsic scale of land cover variation in the study area being smaller than 30 m. To test whether the results stemmed purely from training class definition or whether the algorithm itself was inappropriate for classifying land cover in the study area, the ANN was reset and trained with exactly the same pixels (acquired in region/polygons) that were used to train the ML classifier.

7.4.2. ANN trained with the training data used for ML classification

Following training and validation, a more of realistic set of results was observed. Figures 7.2 to 7.5 show the classified images for Landsat TM from 1988, 1992, 1996 and 2000, derived from the re-trained network. Again, the aim was not to produce a map of all land cover in the region but rather to locate the change in the vegetation cover classes that were relevant and likely to be affected by groundwater lowering. For that reason the following analysis will focus mostly on the OT, CF, AC and PLNV classes. The forest class has been ignored because the area covered with this class is very small.

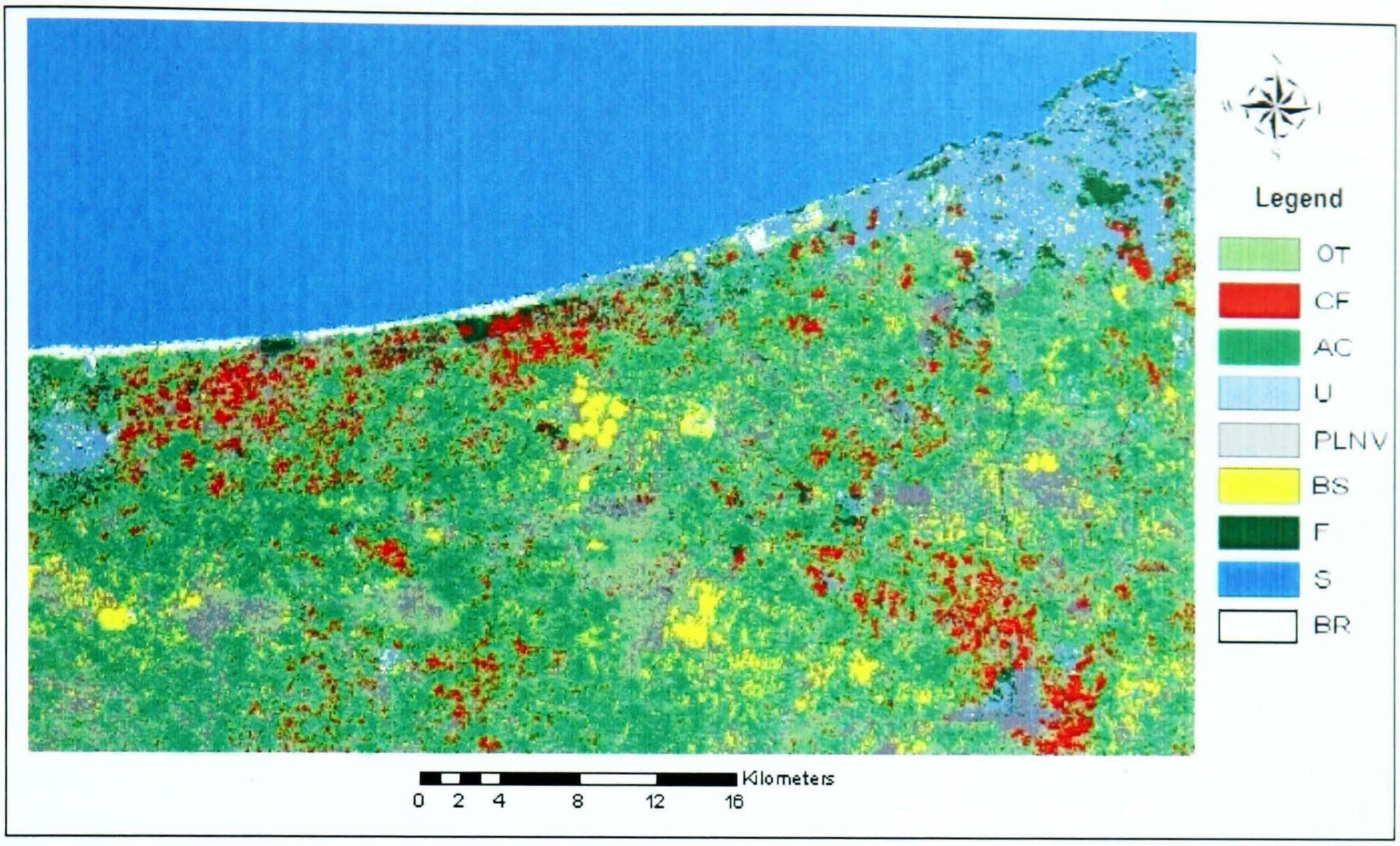

Figure 7.2. Land cover map derived from the ANN classification of Landsat TM5 1988 image (trained using the same training data as ML classification).

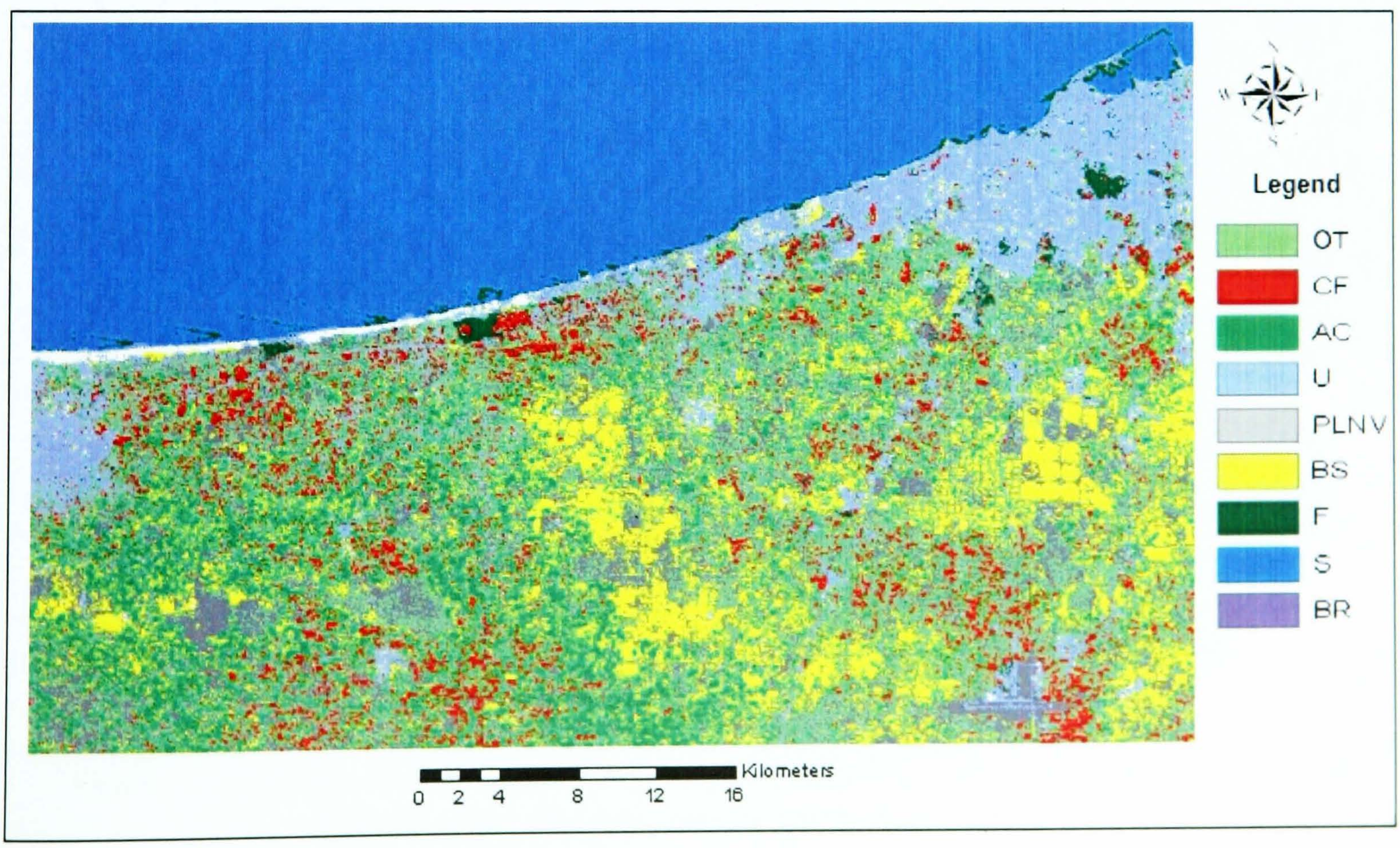

Figure 7.3. Land cover map derived from the ANN classification of Landsat TM5 1992 image (trained using the same training data as ML classification).

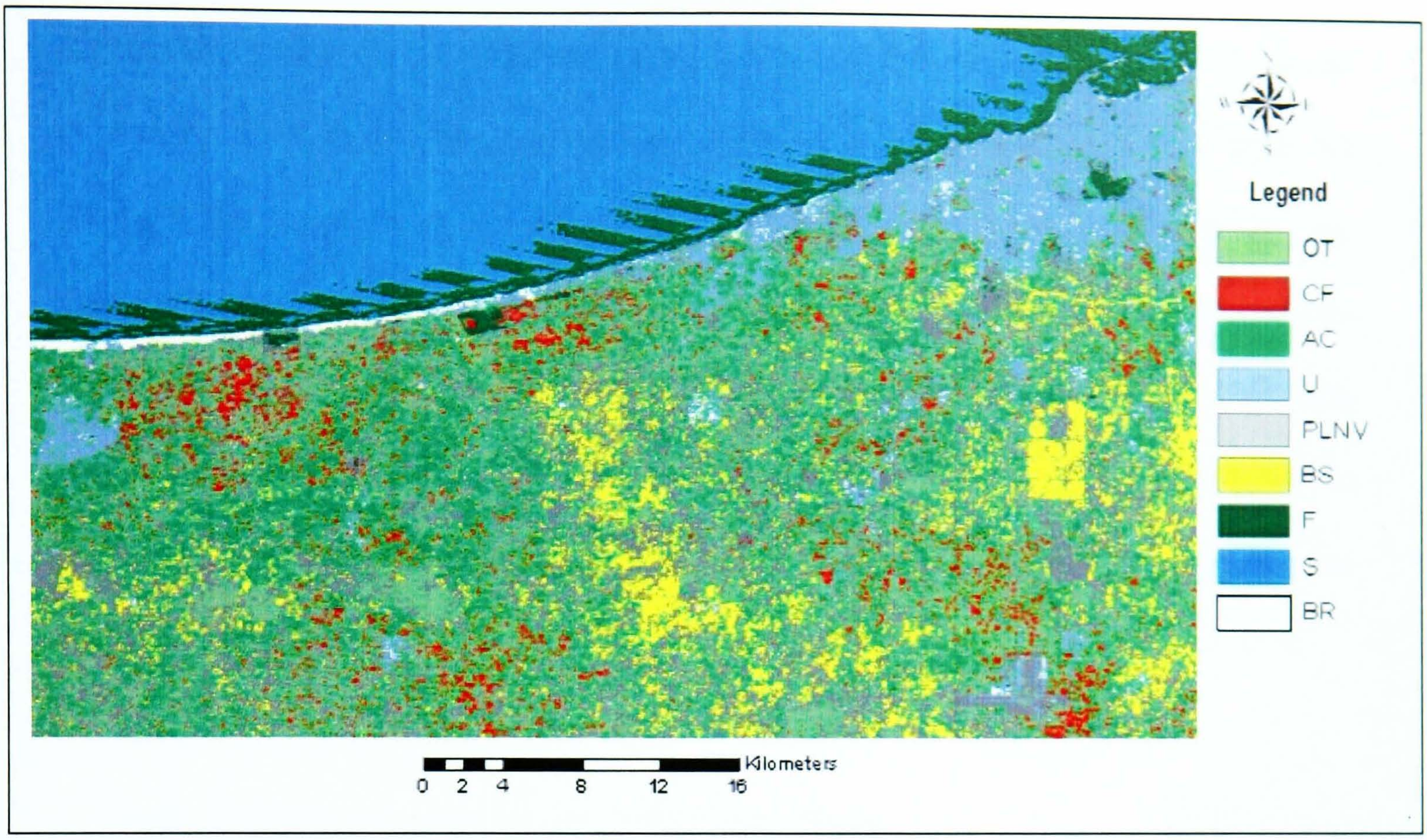

Figure 7.4. Land cover map derived from the ANN classification of Landsat TM5 1996 image (trained using the same training data as ML classification).

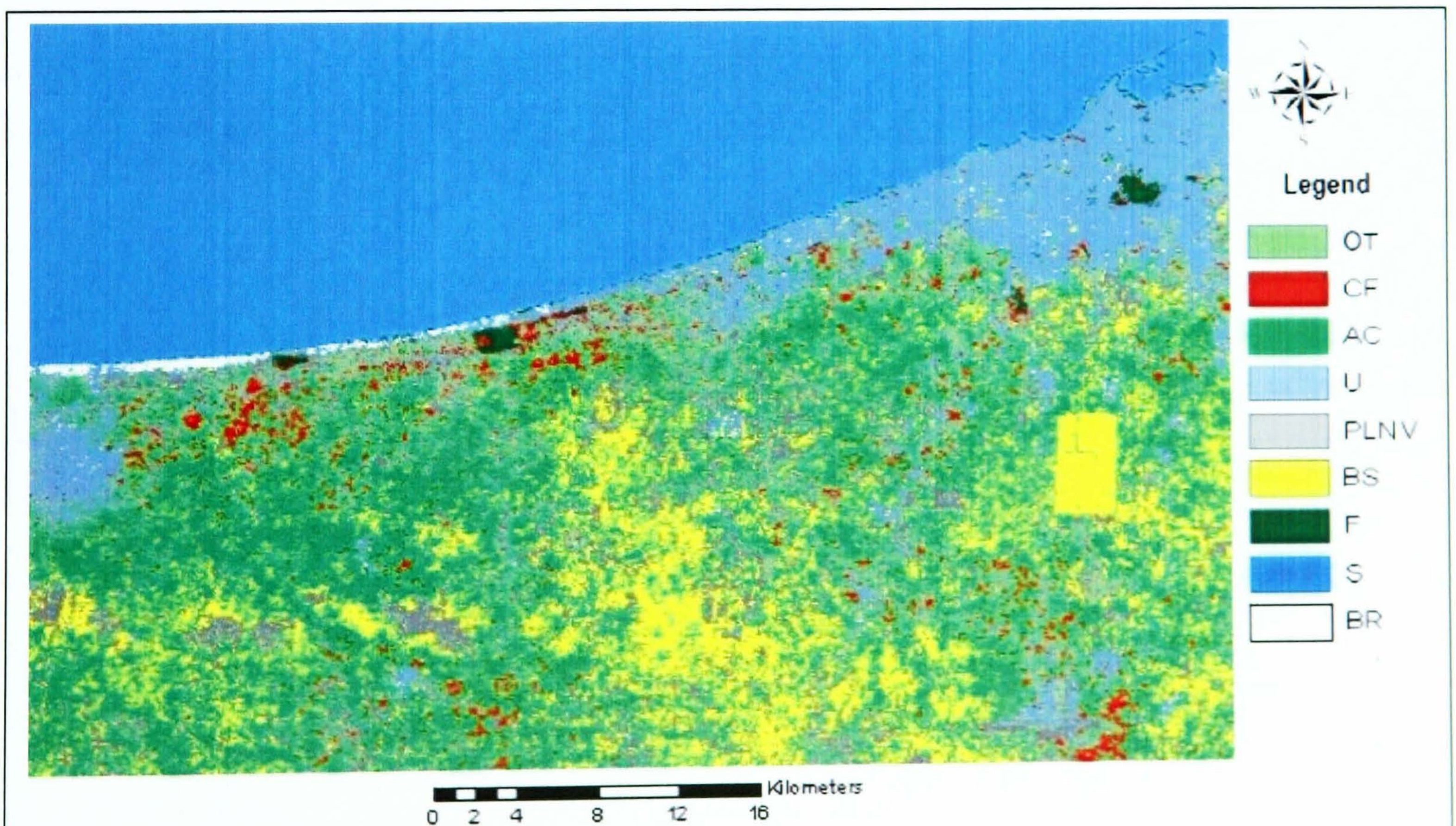

Figure 7.5. Land cover map derived from the ANN classification of Landsat TM5 2000 image (trained using the same training data as ML classification).

7.4.3. Accuracy assessment

The accuracy of each classification (trained using the ML training data) for all images was determined by running the testing (validation) data through the ANN once the network had been trained. There is a clear confusion between some classes, e.g. between the sea and forest classes, which are located near to the shoreline. There is also some confusion due to residual noise (striping), particularly in the 1992 and 1996 data which results from the incorporation of texture (GLCM) information, in addition to purely spectral data. The classification confusion matrix for each image is presented in Tables 7.3–7.6.

Table 7.3. Confusion matrix for the 2000 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	80	3	4	0	13	0	0	0	0	80
CF	1	93	6	0	0	0	0	0	0	93
AC	8	4	87	0	1	0	0	0	0	87
U	2	0	0	93	0	0	3	0	2	93
PLNV	11	0	0	0	84	5	0	0	0	84
BS	0	0	1	0	2	97	0	0	0	97
F	0	0	0	3	1	0	88	0	8	88
S	0	0	0	0	0	0	0	100	0	100
BR	0	0	0	4	0	0	3	0	93	93
Producer's Accuracy %	78	93	89	93	83	95	94	100	90	

Table 7.4. Confusion matrix for the 1996 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	88	10	2	0	0	0	0	0	0	88
CF	4	89	5	0	2	0	0	0	0	89
AC	3	7	82	3	5	0	0	0	0	82
U	0	0	0	97	0	0	2	0	1	97
PLNV	4	3	0	0	91	2	0	0	0	91
BS	0	0	2	1	0	97	0	0	0	97
F	0	0	0	0	0	0	100	0	0	100
S	0	0	0	0	0	0	0	100	0	100
BR	0	0	1	4	0	0	0	0	95	95
Producer's Accuracy %	89	82	89	92	93	98	98	100	99	

Table 7.5. Confusion matrix for the 1992 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	78	4	6	1	10	1	0	0	0	78
CF	11	79	1	1	1	0	7	0	0	79
AC	6	4	84	1	1	2	2	0	0	84
U	0	0	0	100	0	0	0	0	0	100
PLNV	3	1	0	0	95	1	0	0	0	95
BS	1	0	0	3	3	93	0	0	0	93
F	2	2	0	0	2	0	94	0	0	94
S	0	0	0	0	0	0	0	100	0	100
BR	0	0	0	8	0	0	0	0	92	92
Producer's Accuracy %	77	88	92	88	85	96	91	100	100	

Table 7.6. Confusion matrix for the 1988 classified image.

Land cover class	OT	CF	AC	U	PLNV	BS	F	S	BR	User's Accuracy (%)
OT	84	3	6	0	7	0	0	0	0	84
CF	2	81	9	0	0	0	8	0	0	81
AC	1	7	83	2	2	2	3	0	0	83
U	0	0	0	97	1	0	0	0	2	97
PLNV	12	1	0	0	83	4	0	0	0	83
BS	0	0	0	0	0	96	0	0	4	96
F	1	3	0	1	2	0	93	0	0	93
S	0	0	0	0	0	0	0	100	0	100
BR	0	0	0	7	0	0	0	0	93	93
Producer's Accuracy %	84	95	85	91	87	94	89	100	94	

Each image shows that for most classes there is some misclassification, especially between the four vegetation classes of interest (OT, CF, AC and PLNV). The majority of the confusion is between the classes OT with AC and PLNV (Table 7.3 to 7.6), but also between CF with AC, rather than OT with CF. The majority of confusion between the annual crops and natural vegetation is likely to be due to the growth of vegetation in the spaces between the lines of trees, showing a similar influence on the classification as noted using the ML classification approach.

The overall accuracies for 1988, 1992, 1996, and 2000 were, respectively, 90%, 90.6%, 93.2%, and 90.6%, with corresponding Kappa statistics of 0.88, 0.89, 0.92 and 0.89 (Table 7.7). User's and producer's accuracies of individual classes were generally high.

Table 7.7. Summary of user's, producer's and overall accuracy (%) and Kappa statistic value for each image classification.

Land cover Class	1988 Producer's	1988 User's	1992 Producer's	1992 User's	1996 Producer's	1996 User's	2000 Producer's	2000 User's
OT	84	84	77	78	89	88	78	80
CF	95	81	88	79	82	89	93	93
AC	85	83	92	84	89	82	89	87
U	91	97	88	100	92	97	93	93
PLNV	87	83	85	95	93	91	83	84
BS	94	96	96	93	98	97	95	97
F	89	93	91	94	98	100	94	88
S	100	100	100	100	100	100	100	100
BR	94	93	100	92	99	95	90	93
Overall accuracy %	90		90.6		93.2		90.6	
Kappa statistic	0.88		0.89		0.92		0.89	

7.4.4. Changes in class extent

The four classes of interest (OT, CF, AC and PLNV) show a clear and visible change through the period (Figure 7.6, Table 7.8). The change in classes OT, CF and PLNV show overall decreases between 1988 and 2000, which mirrors the results observed in Chapter 6. The AC class shows an overall increase in the same period, as noted previously (Figure 7.7).

Table 7.8. Area (ha) of classes in each year.

	1988	1992	1996	2000
OT	29579	38368	32881	23502
CF	8562	7255	5414	4016
AC	20517	8740	15161	20973
U	9187	14058	11256	14945
PLNV	24940	17787	28312	21187
SD	6753	15828	9116	17832
F	3009	1535	5903	729
S	45708	45245	40496	45877
BR	1394	834	1102	589

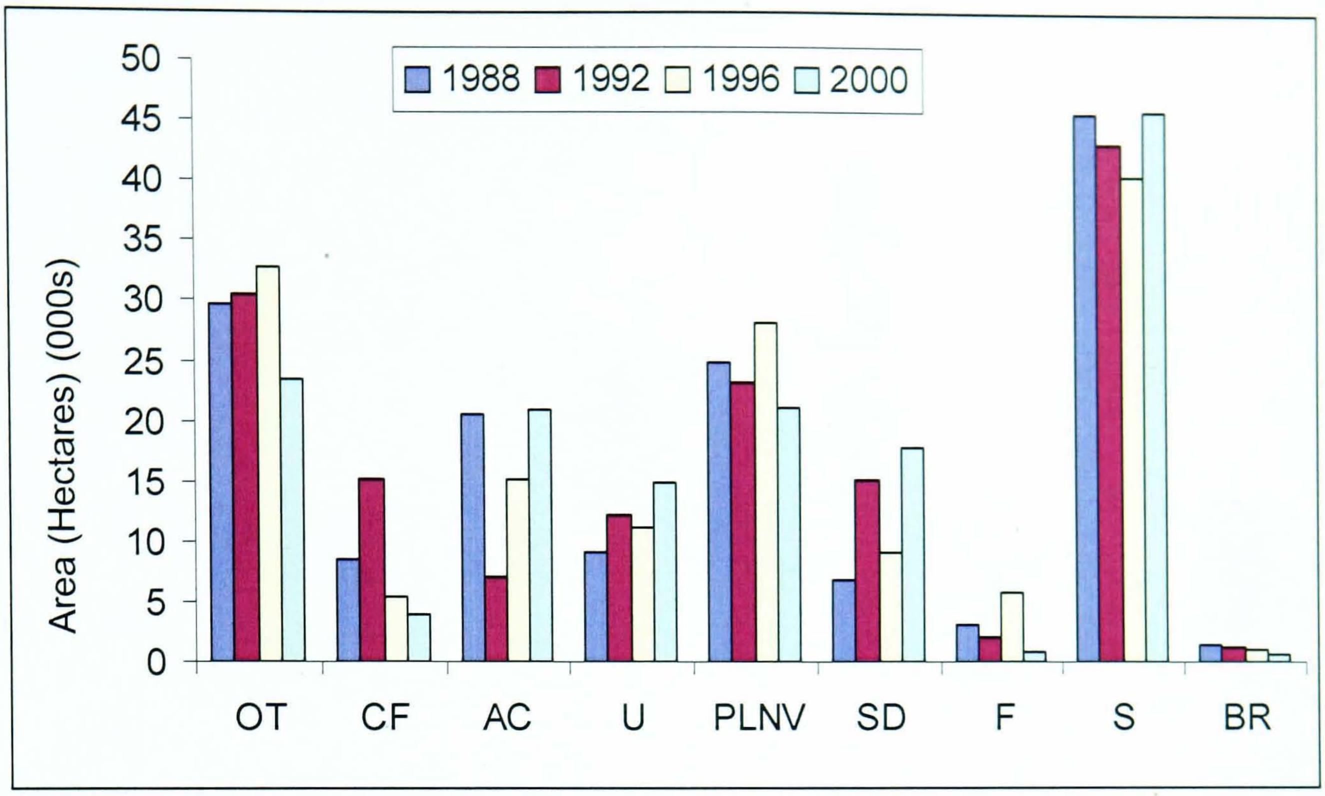

Figure 7.6. Changes in extent of classes from 1988 to 2000.

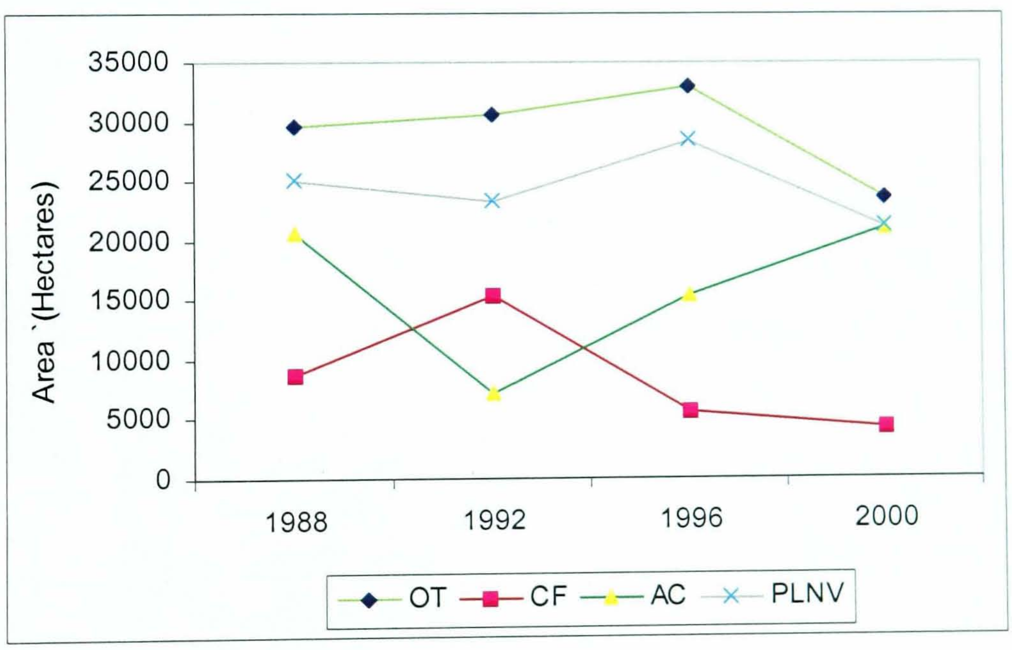

Figure 7.7. Change in OT, CF, AC and PLNV classes from 1988 to 2000.

Vegetation classes OT, CF, PLNV and F have decreased in their extent (Figure 7.8), decreasing by 21%, 53%, 15% and 76%, respectively, from 1988 to 2000. At the same time AC increased by 2%. Figure 7.9 shows the negative and positive change in CF class and illustrates a clear decrease in the area of the class over the time period.

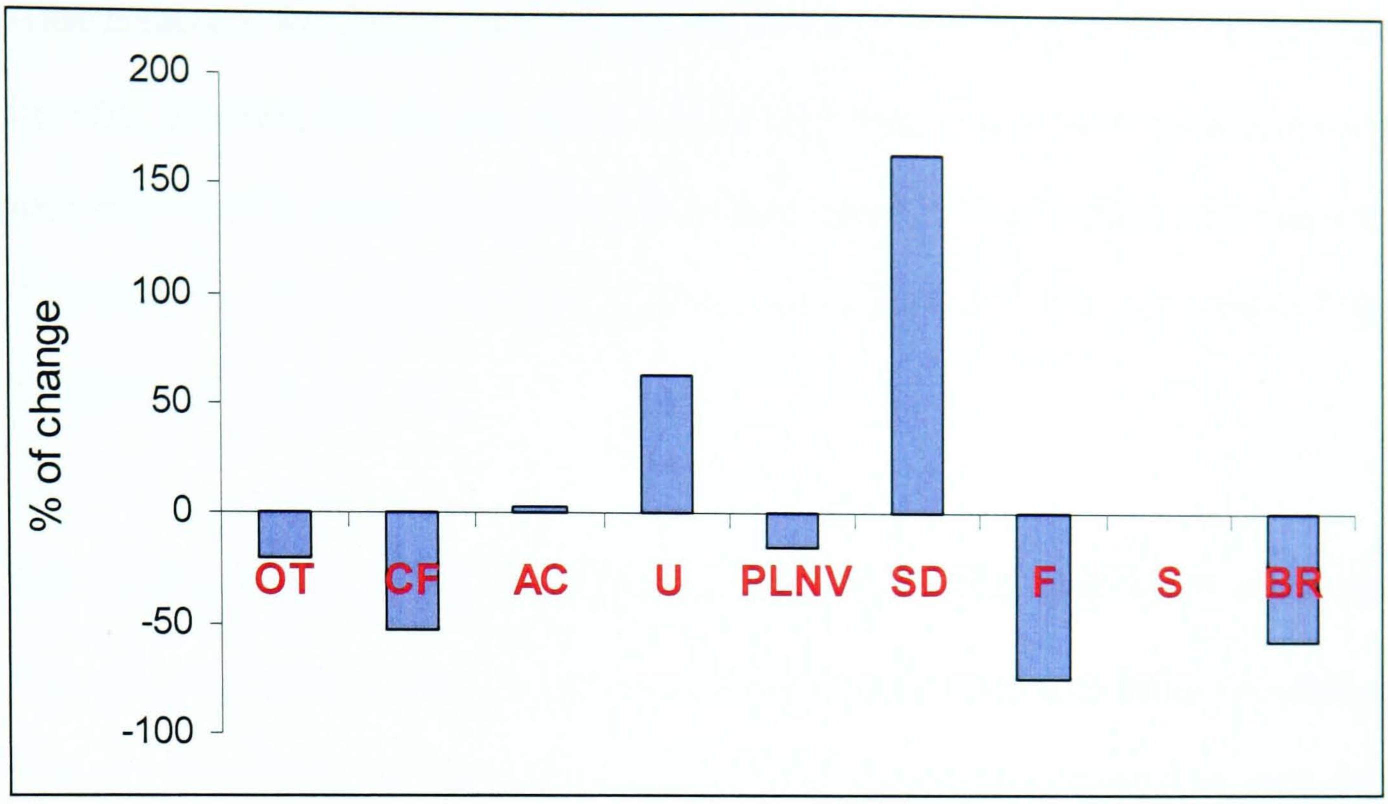

Figure 7.8. Percentages change in areal extent of land cover classes from 1988 to 2000.

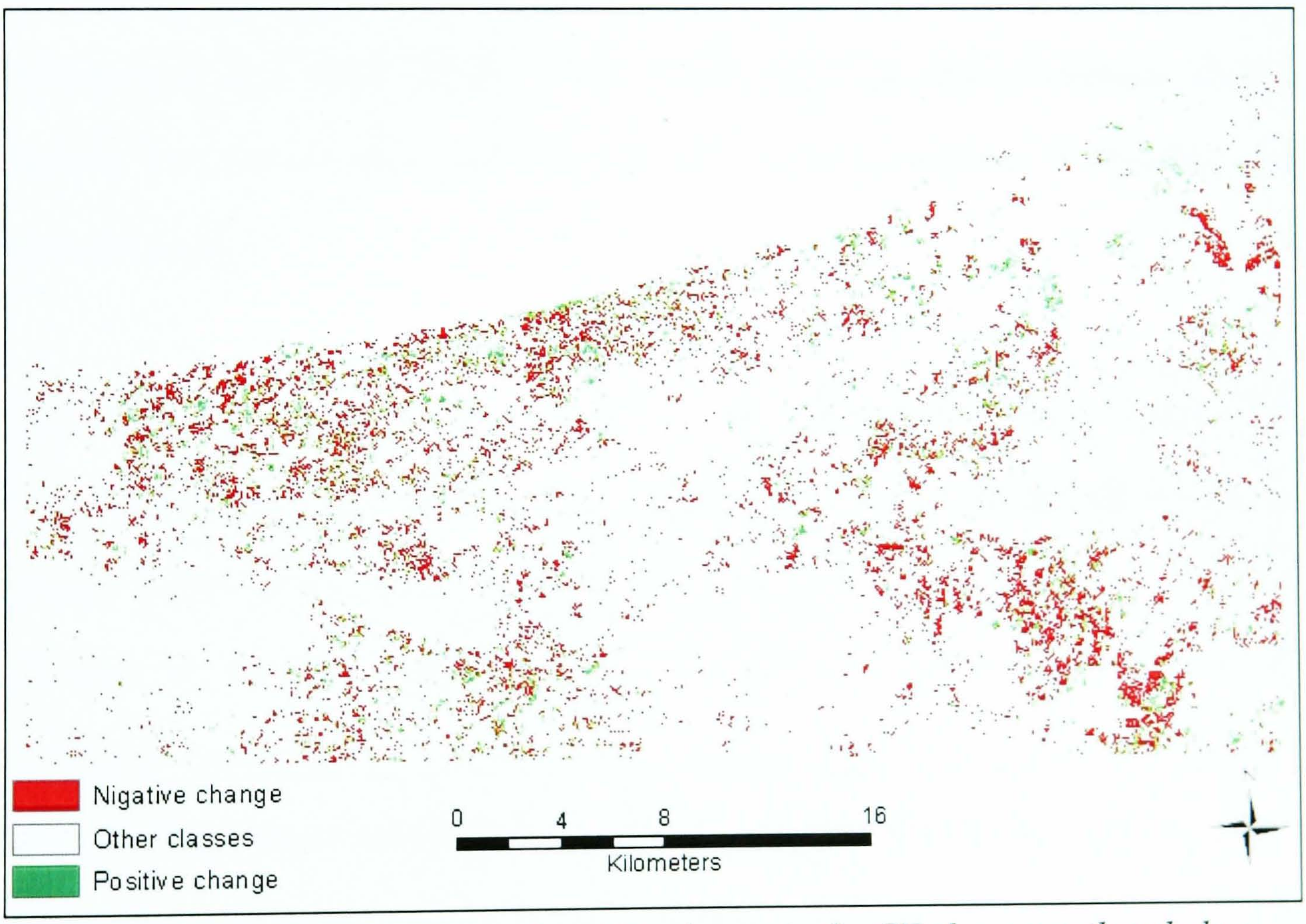

Figure 7.9. The negative and positive change in the CF class over the whole study area from 1988 to 2000.

Changes in other classes, however, varied from those observed using the maximum likelihood classification. For example, the ANN results show an increase in forest between 1992 and 1996, with a reduction in sea area (Table 7.8), but this is attributable to the presence of striping as noted previously. There is also significant overlap between the urban and bare rock classes, which seems to indicate a decrease in urban areas and a decrease in the BR class between 1992 and 2000 (Table 7.8). This, however, contradicts all available evidence with respect to urban encroachment in the area around Tripoli (Vaughan and Oune, 1998).

7.5. Comparison of the classification results of ML and ANN methods

Chapters 6 and 7 have detected land cover change in the study area using two different methods. The ANN and ML classification methods are now compared to each other. General comparison was made by considering the accuracy of the results only (overall accuracy, the amount of change/pattern of the land cover) and not intended to be compared directly. Other criteria which might be used to compare methods, such as training time, the amount of training data required and the software availability, were not considered.

The overall classification accuracy of the ML method varied between 67% and 76%, while the overall classification accuracy using the ANN method was 90% to 93% for all images. Consequently, the ANN classifier provides results of higher accuracy than those provided by the ML classifier, similar to observations made by, for example, Berberoglu *et al.* (2000), Chiuderi (1999), Foody *et al.* (1992), and Kavzoglu and Mather (1999). This is also confirmed by the Kappa statistic, a commonly used measure to compare between the accuracies of two different classifiers (Mather, 2004), which was greater for the ANN than for the ML. Comparing the training datasets used to run both methods, the training datasets which used to run the ML classifier were more than those used for ANN classifier. While 200 pixels which selected randomly from the total of the same polygon areas were used to train and test the ANN classifier.

Patterns of land cover change over time were comparable and realistic with reference to the questionnaire results and field data. Both results illustrate a similar pattern of change of land cover, especially in the vegetation cover which might be related to changes in groundwater levels. Although the results from both methods were not exactly the same, the general trends and magnitudes of change in most classes were very similar. For example, the percentage of change in areal extent of OT, CF, U, PLNV, F and BR classes from 1988 to 2000 are largely similar, whilst AC and BS classes extent was somewhat different which might related to misclassification in both classifiers and depends on the space between the lines of trees (Figure 6.10)

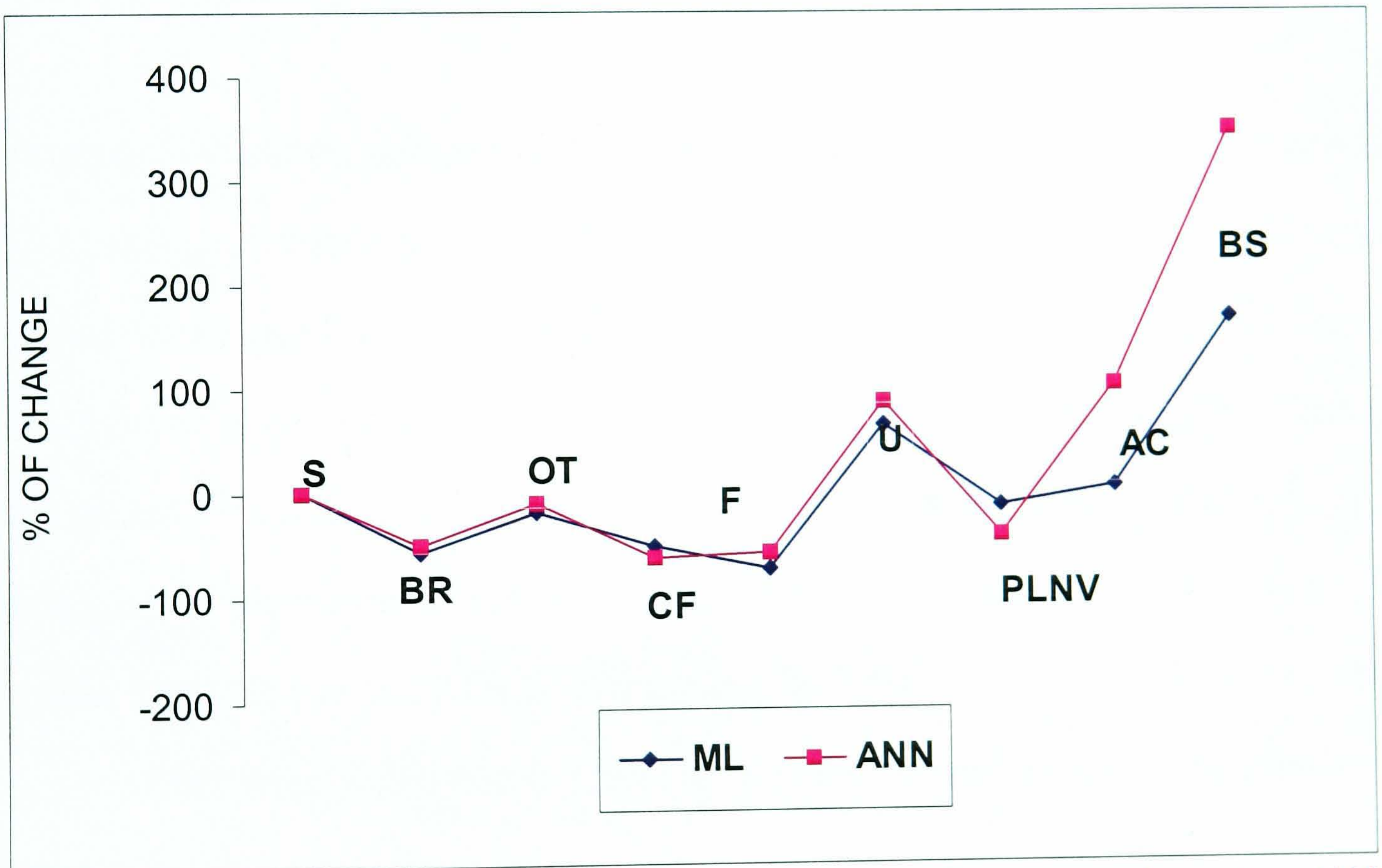

Figure 6.10. Comparison of percentage change in areal extent of land cover classes from 1988 to 2000 as determined by ML and ANN.

Figure 7.11 illustrates the agreement in the classification results for the CF class only, derived from both classification methods. By subtracting the ML change map from ANN change map to show pixels which are in agreement, it shows that both methods provide similar results and therefore the amount of change that has taken place in the

CF class. The areas that are not in agreement are likely to be the result of the different algorithm's ability to deal with mixed pixels, particularly around field boundaries. The fact that the magnitude of change is largely consistent, and that there are no defined spatial patterns to the disagreement, suggest that both methods provide a robust methodology to mapping change, despite very different approaches to classification (i.e. statistical versus neural).

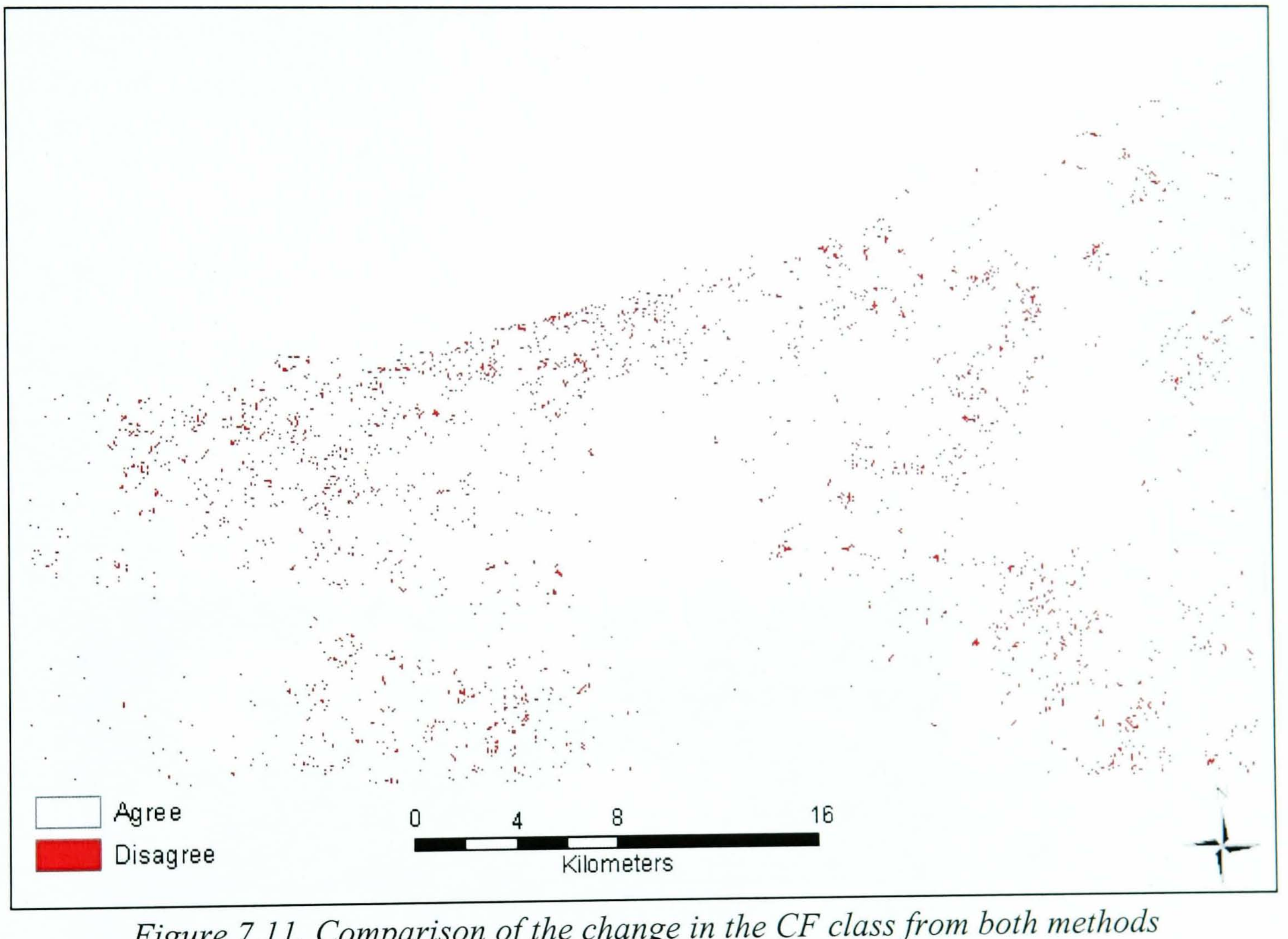

Figure 7.11. Comparison of the change in the CF class from both methods (ML and ANN) over the whole study area.

The results from both methods were also compared at a local (farm) scale. For example, at Farm A, both results show a similar pattern in terms of class extents, but are not exactly the same, with the ANN result seeming to give a less 'coherent' pattern of land cover, compared to the more homogenous appearance of land cover in the ML results (Figure 7.12a and 7.12b). From visual comparison with the high spatial resolution image (Figure 7.13), it could be argued that the ANN result provides a more 'realistic' pattern of the heterogeneous land cover. The area of each class at Farm A from the 2000 image was calculated from both ANN and ML classifiers. Table 7.9 shows the similarity of the estimated extent of the classes of interest from both methods, particularly in the classes of interest (except PLNV).

Table 7.9. Estimated areas (ha) of land cover at Farm A, using both classification methods (image 2000).

Class	ANN	ML
OT	9.18	10.98
CF	1.15	1.53
AC	4.41	3.15
U	0.45	0.99
PLNV	6.75	3.33
SD	0.9	2.34
BR	0.0	0.36

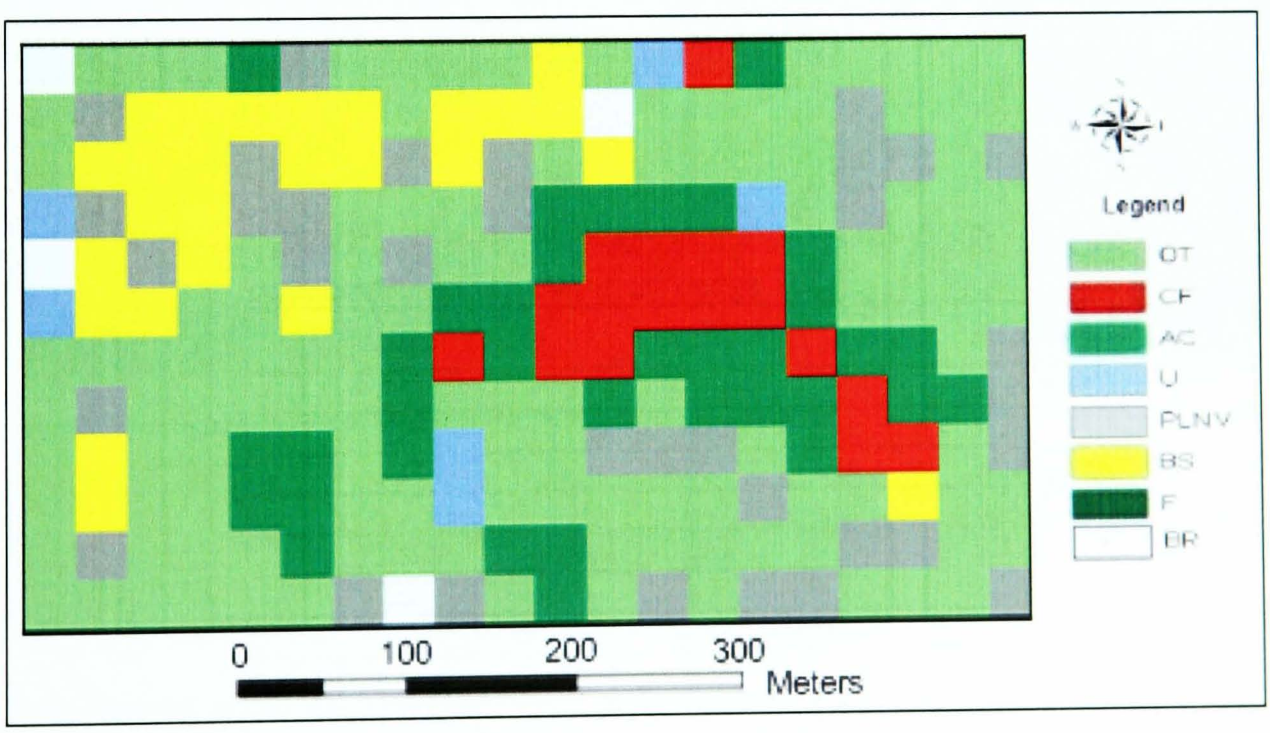

Figure 7.12a. The classified Landsat TM image from 2000 at Farm A using the ML classification.

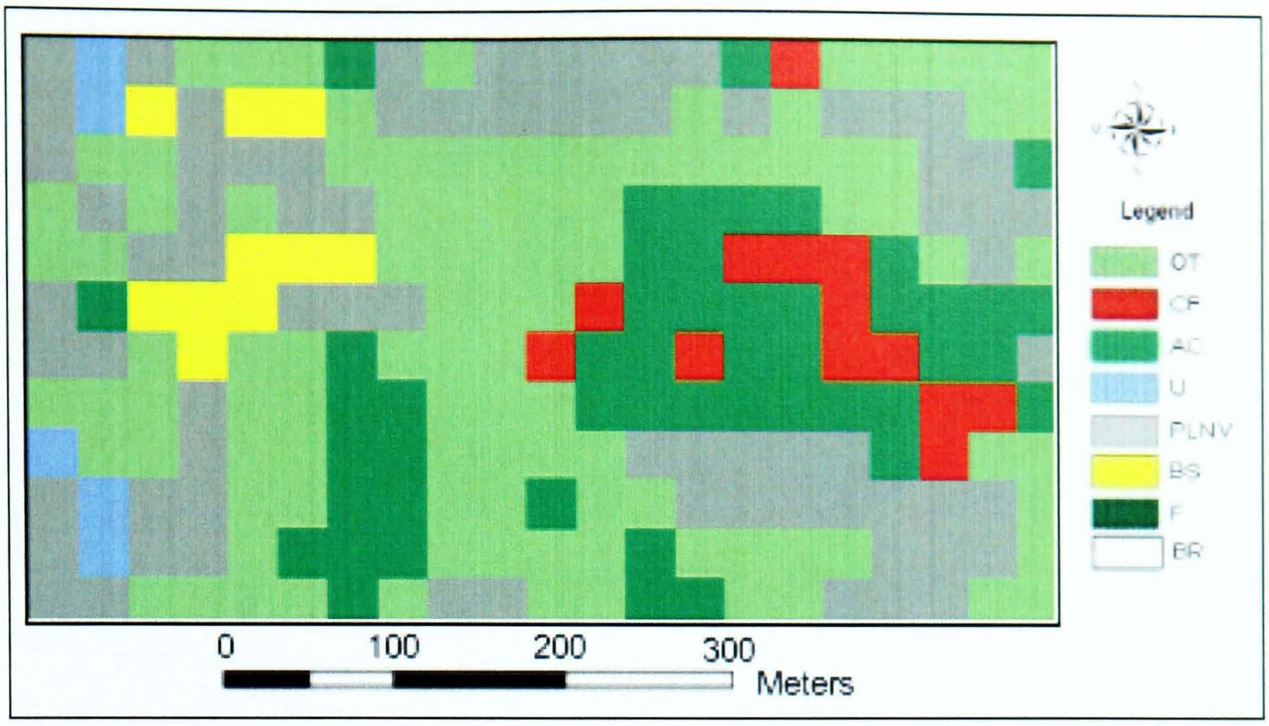

Figure 7.12b. The classified Landsat TM image from 2000 at Farm A using the ANN classification.

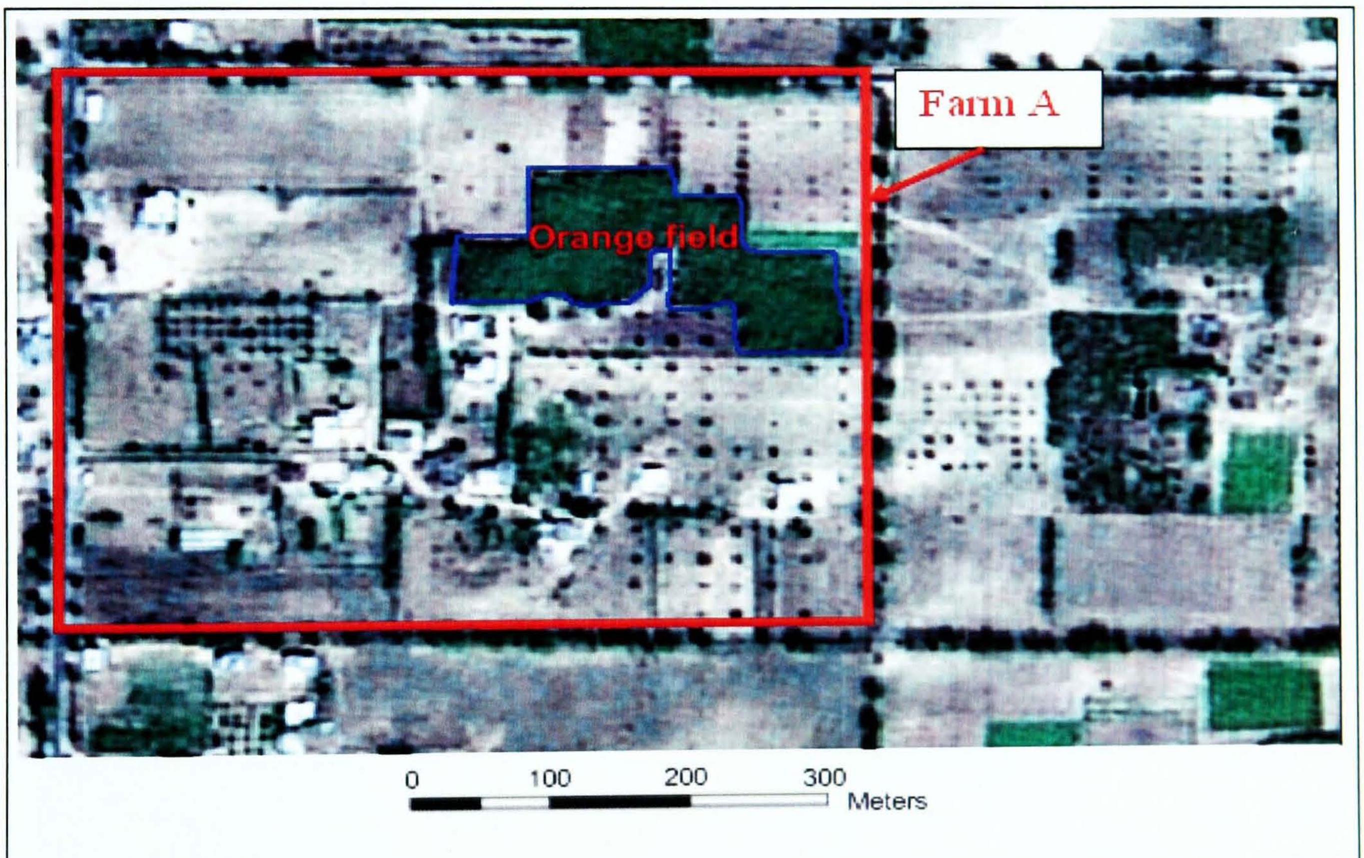

Figure 7.13. SPOT 5 image of Farm A (acquired 2002).

Farm C, visited as part of the field visit and containing fields of orange trees (CF class), was also analysed (Figure 7.14). The area covered by the CF class observed from both classifications is similar as shown in Figure 7.15a and 7.15b and both compare favourably with the high spatial resolution data (Figure 7.16) when a visual comparison is made, particularly for the CF class.

Figure 7.14.Orange trees at Farm C (looking due west, 5^{th} July 2006).

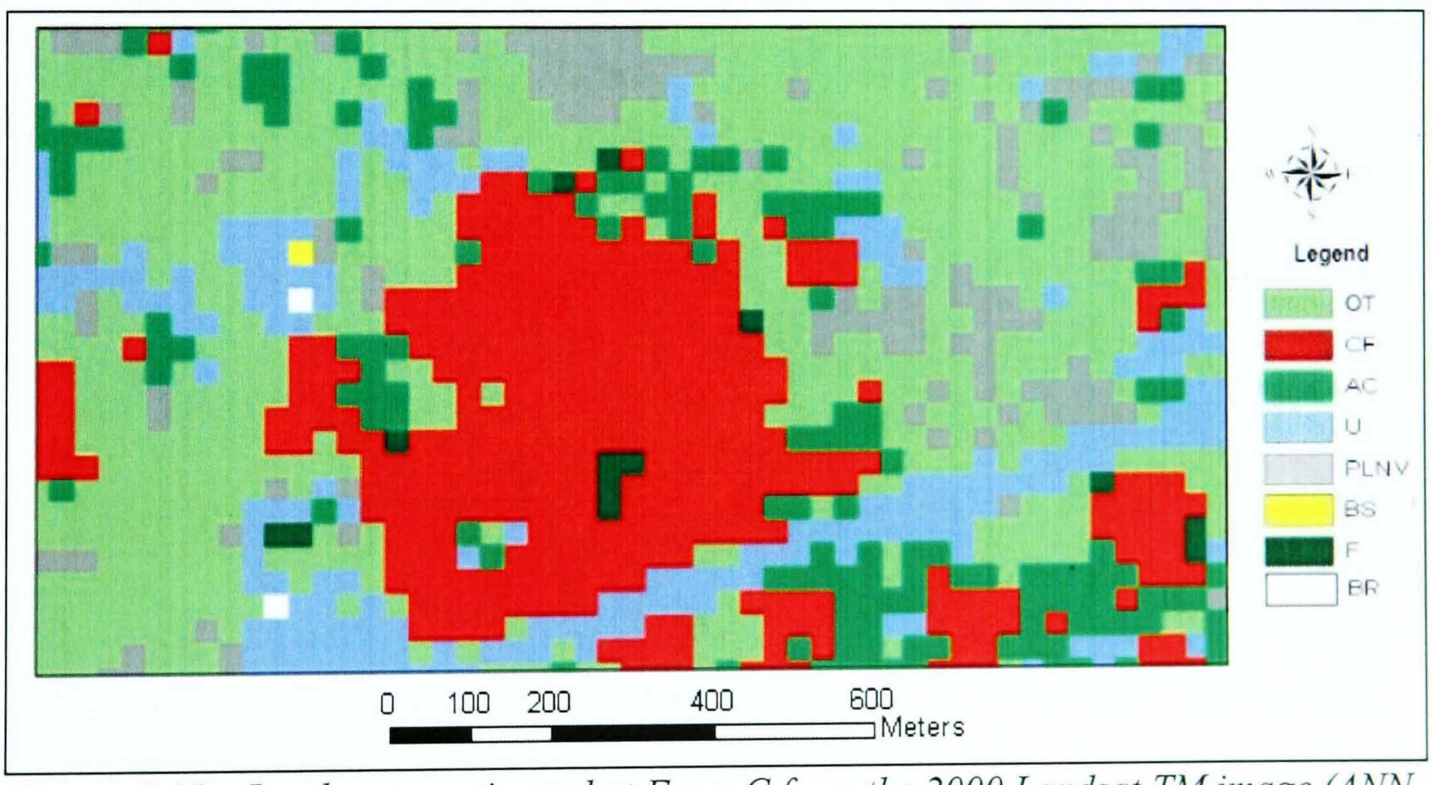

Figure 7.15a. Land cover estimated at Farm C from the 2000 Landsat TM image (ANN classification).

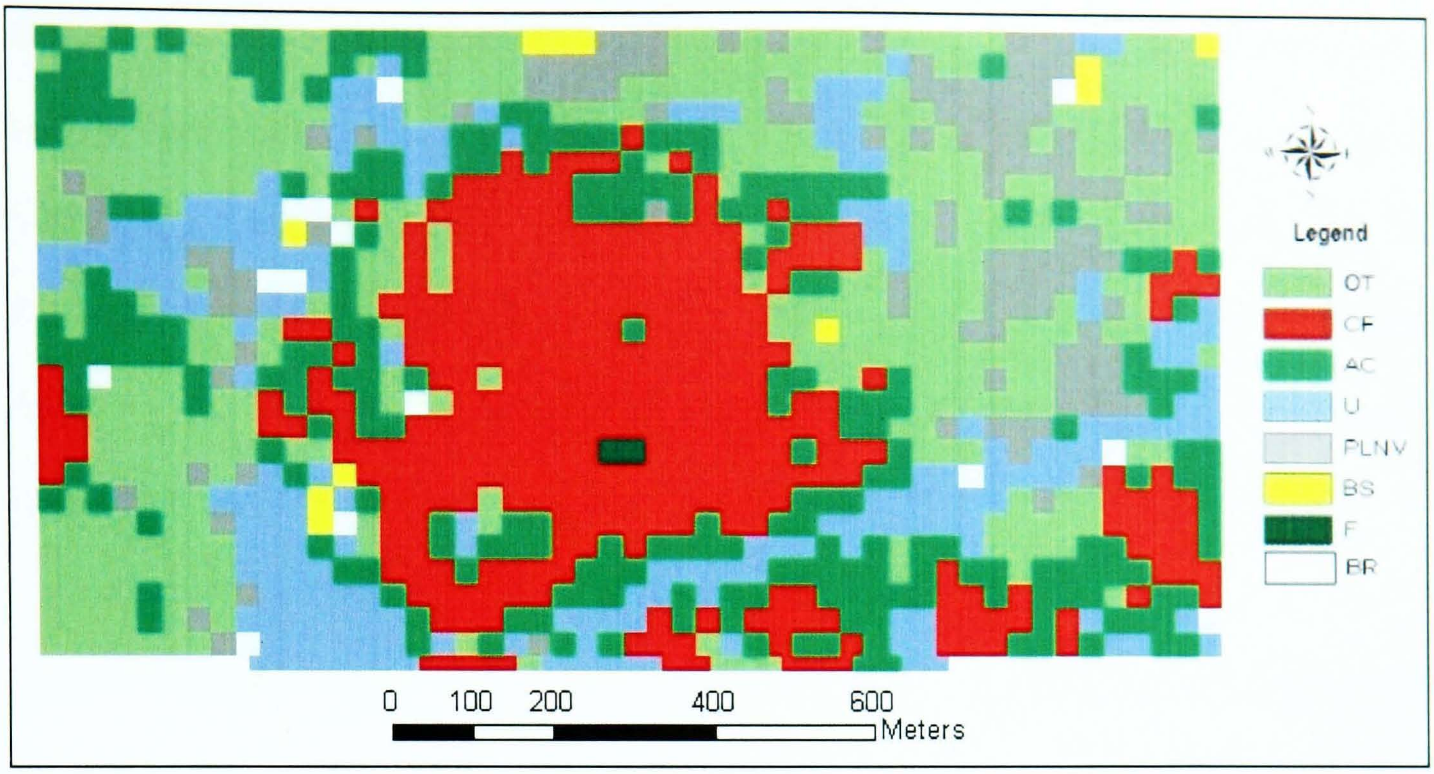

Figure 7.15b. Land cover estimated at Farm C from the 2000 Landsat TM image (ML classification)

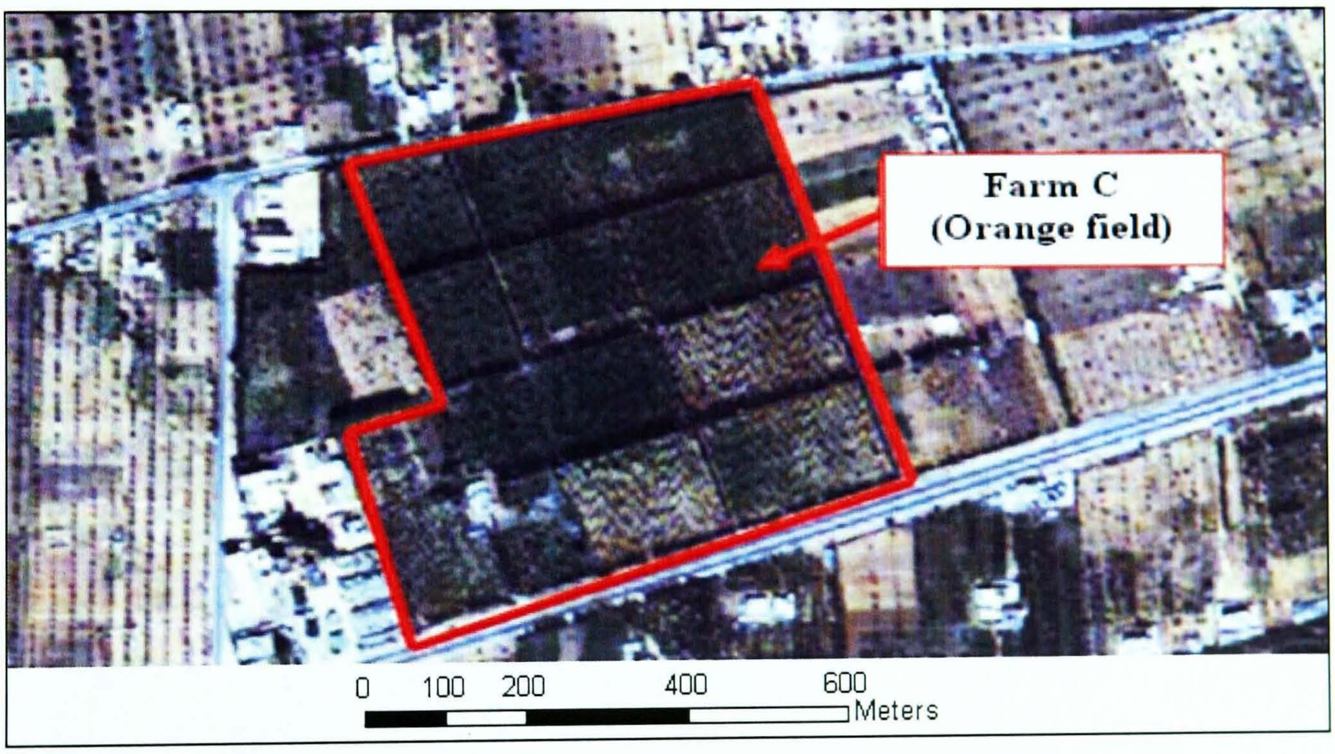

Figure 7.16. Farm C depicted by QuickBird, illustrates the fields of orange trees in 2002

As mentioned earlier, there is a significant overlap between urban areas and the bare rock class. However the ANN method results in less confusion than the ML algorithm. The bare rock areas are generally located near to the shoreline rather than in the rest of the study area. The ANN results mapped the BR class less toward the inland areas than the ML results, particularly in the urban areas (Tripoli city centre). By comparing the results from both methods (Tables 6.8 and 7.8) the extent of the BR class is more realistically mapped using the ANN than ML. In addition, the lowest user's accuracy of this class from ANN was 92% and the lowest producer's accuracy was 90%, whilst from the ML the lowest was 90% for the user's accuracy and 54% for the producer's accuracy.

A good example of this can be seen at Farm E. Here, the ML classified image shows a much larger number of pixels classified as BR than those classified using the ANN methods (Figure 7.17a and 7.17b). In comparison with the high spatial resolution QuickBird image (Figure 7.18), it is clear that there has been significant confusion between urban and bare rock areas, with the ANN providing a more realistic interpretation of land cover at this site. Given that the spectral properties of both classes are similar, it is possible that the added texture measures used as an additional input to the ANN (Section 7.3) provide improved discrimination for these classes.

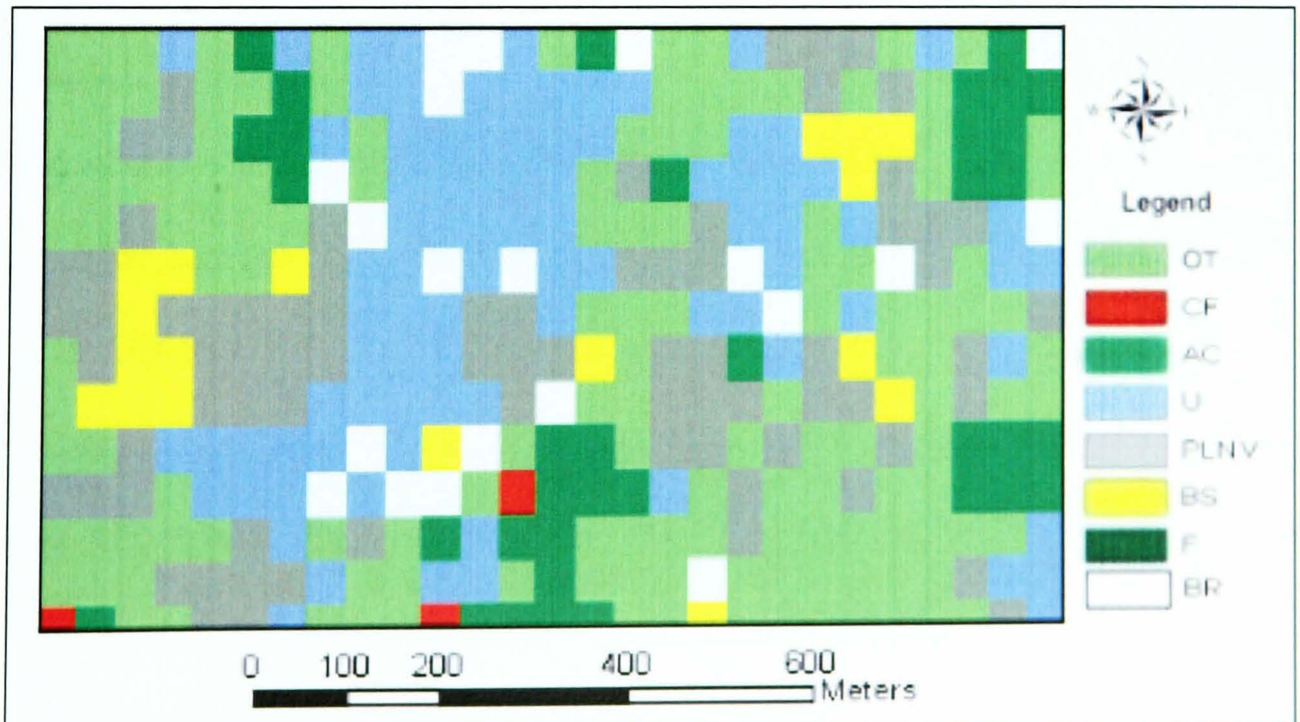

Figure 7.17a. ML classified image, illustrating the confusion between urban and bare rock classes (Farm E).

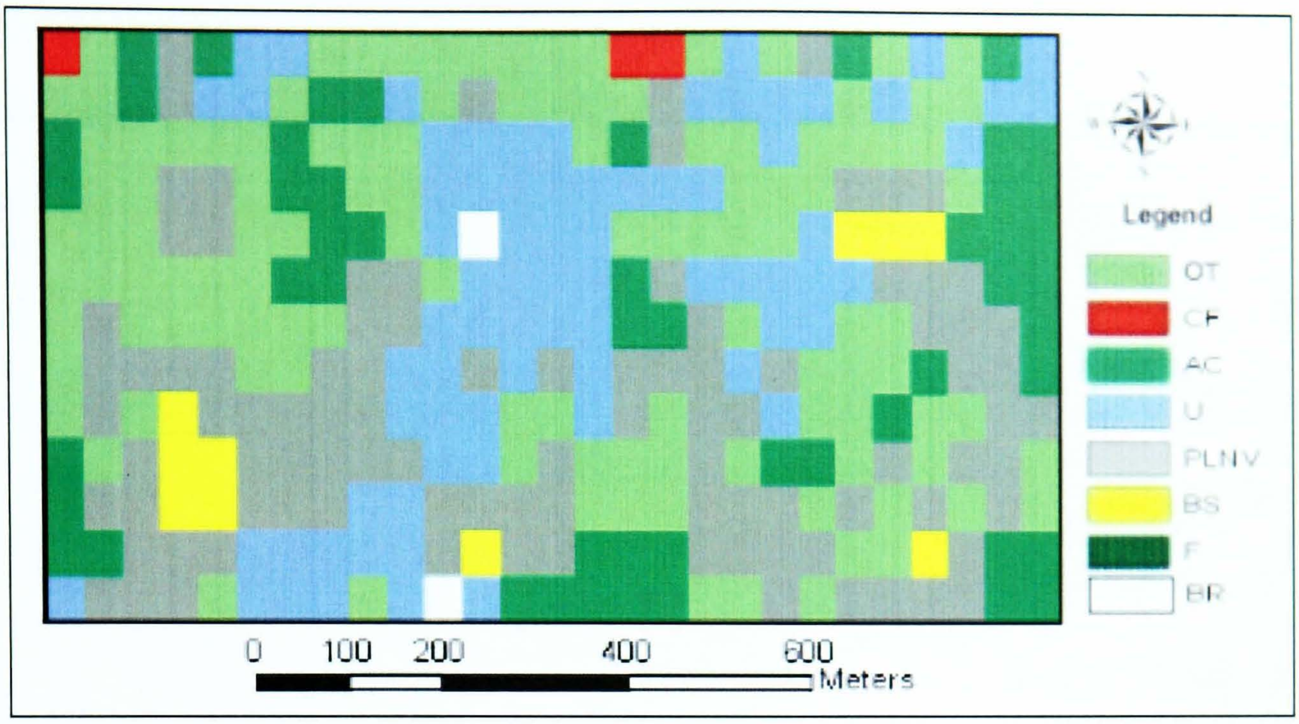

Figure 7.17b. ANN classified image, illustrating the confusion between urban and bare rock classes (Farm E).

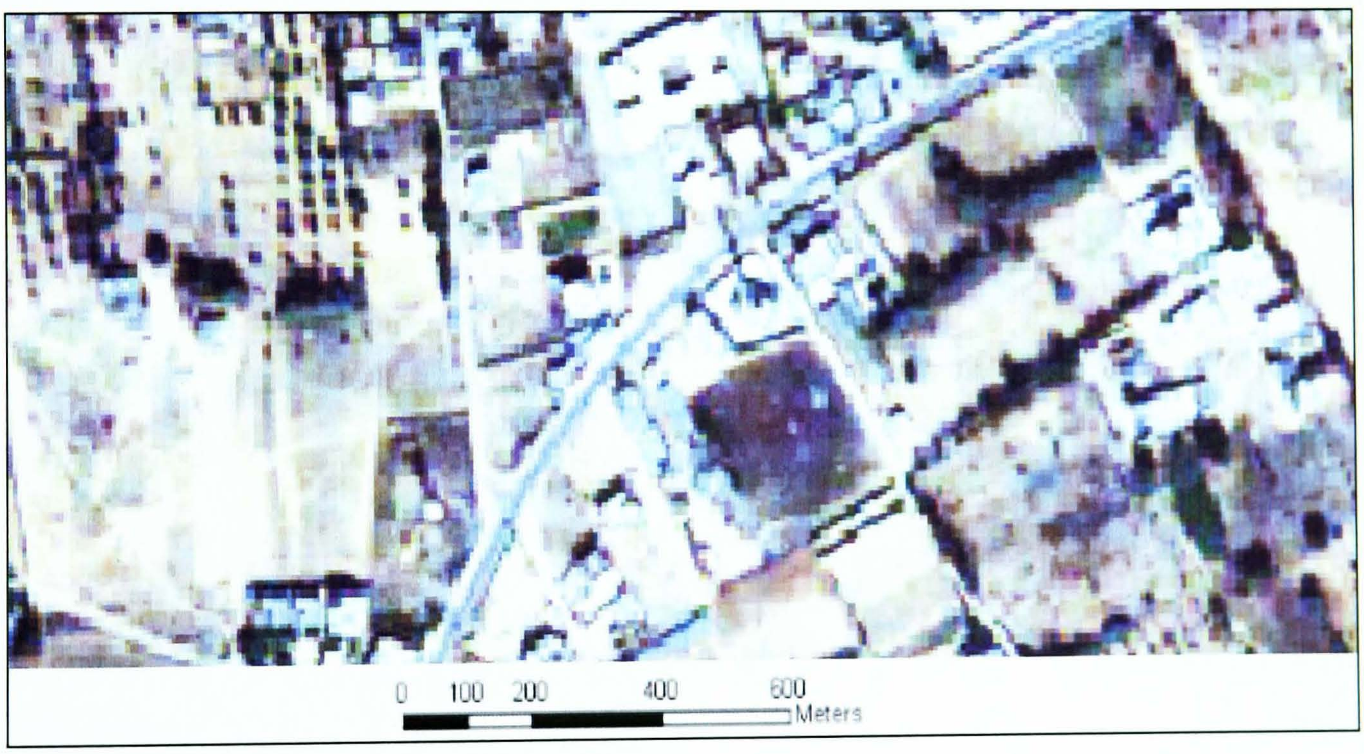

Figure 7.18. Farm E depicted by QuickBird, illustrating the urban extent in 2002.

7.6. Summary

The neural network was able to classify land cover with a high accuracy using Landsat TM imagery. The classification was based entirely on the internal "training" by the network from the specific training set. The results observed were dependent on the method of collecting the training set and the method of learning used by the network to classify the data. The individual pixel method of collecting training datasets provided unrealistic results compared with the ML results and questionnaire responses. For example, at the farm scale, results indicated that the DT, CF and PLNV classes increased, and the urban class decreased, which was not realistic (Vaughan and Oune, 1998). Using the training dataset selected as polygons, which were used for the ML classifier, offered better and more consistent results. The ANN classifier gave results with high accuracy (over 90%) and an excellent Kappa value over 0.88, greater than those from the ML. This supports the findings of others that the ANN classifier can produce land cover maps more accurately than the ML classifier (e.g. Berberoglu *et al.*, 2000; Chiuderi 1999; Foody *et al.*, 1992; Kavzoglu and Mather, 1999). Both methods provided consistent and comparable results of land cover changes at the landscape scale, but revealed subtle variations at the farm scale, although, in general, the estimations of class extents were comparable. As a result, the overall pattern of land cover change can be considered a realistic interpretation of the change in land cover that has occurred in the Jeffara Plain between 1988 and 2000.

CHAPTER EIGHT

Discussion

8.1. Introduction

The majority of previous studies have been interested in the effects of land surface activities upon the groundwater (Al-Senafy and Abraham, 2004; Candela *et al.*, 2008; Ma *et al.*, 2005; Mahvi *et al.*, 2005) i.e. effects of land cover change in groundwater quantity and quality (salinity and pollution). This project however, has determined that there has been significant land cover change in the Jeffara plain region of Libya, both in terms of perceived change in agricultural practices, and observed change as characterised using remote sensing that is likely to be the result of groundwater change. Whilst the general pattern of change observed and perceived is similar, it is important to try and more formally link such changes to the availability and quality of groundwater in the region, which may then provide the basis for modelling change and future predictions.

8.2. Pattern of land cover change in the Jeffara Plain

Land cover change as an environmental variable is a vital factor and often the most significant environmental variable that can impact the biodiversity of landscape (Chapin *et al.,* 2000). Multi-temporal remotely sensed data have been used to identify changes in land cover by image classification. The results show the general change in pattern of land cover particularly in vegetation classes (mainly agricultural classes) which are affected by groundwater changes (questionnaire survey). For example the change in the CF class over the whole area agreed with observed and perceived changes in groundwater, while the change in this class was higher in the coastal area where the change in groundwater status included the poorer quantity and quality, rather than inland areas where the change was mainly in the quantity. Both Maximum Likelihood and Artificial Neural Networks image classification approaches offered a realistic and largely consistent set of results when compared with the field observations and the questionnaire responses. The ANN provided a more realistic representation of the land cover in a local scale (e.g. Farm E) where there was less confusion than ML classification between the U and BR classes.

The commonly accepted target for classification accuracy is 85% (Thomlinson *et al.*, 1999 cited in Foody, 2002), although there are many studies that use classification results with overall accuracies below the general target (Foody, 2002), particularly in semi arid environments. For example, Ucuncuoglu *et al.* (2006) have used Landsat TM/ETM+ imagery to evaluate the impact of coastal land use in and around Candarli Bay, Aegean Sea on the west coast of Turkey. Classification accuracies of 70% to 73% were reported due to the similar spectral responses of sort of the classes. In thus study the classification accuracies of ML were generally below the target required (between 67% and 76%); this was based upon a pragmatic rather than an ideal approach to accuracy assessment, relying on only a limited set of available validation data. In addition, the ML algorithm is also prone to a number of influences that can affect the accuracy of the outputs, e.g. mixed pixel and atmospheric effects (Foody, 2002), while although every effort (e.g. small training sets and atmospheric correction) to minimize these effects was taken, is likely they still had an effect to an uncertain degree.

As the study area is typically composed of small fields with a high degree of spectral similarity, this made it difficult to distinguish the spectral boundaries between the classes, and hence led to errors from mis-classification (Powell *et al.*, 2004), seen particularly in the results of the DT, CF and AC classes. Due to the pixel size of Landsat images (30 m × 30 m) and the spaces between the lines of trees (5-20 m) in which different kinds of vegetation are present, misclassification and reductions in the accuracy results.

The changes in vegetation classes which are most likely to have been affected by groundwater changes were clearly visible, although these were not consistent for all classes. For example, the OT, CF, PLNV and F class extents decreased during the study period, though the forest class decrease due to anthropogenic effects rather than groundwater changes (questionnaire survey). At the same time the AC class extent increased, particularly due to the farmers utilising the spaces between the rows of trees. In addition, the questionnaire and the hydrological data show that the change in the groundwater level in the coastal area was less than in the inland area, there is still change in the land cover related to changes in the groundwater quality (Figure 5.12 and Figure 5.13) which can be consider as indirect effect of groundwater lowering the coastal area.

The results and the fieldwork observations show that there is no change in the classes of interest in some parts of the study area, for example, some fields of orange trees that have not changed. A farmer in area five reported, "yes, groundwater is getting lower every time, and it is over 200 m below the ground in these days but still can keep growing the orange trees like my farm here (Figure 8.1), however, that will cost more money and possibly, that why farmers stop growing this kind of trees because they need a lot of water".

Figure 8.1. Photos A and B: two sites of a farm where orange trees are still grown although the groundwater level is over 200 m below the ground.

The study area was divided in five area of interest (Figure 6.2.2), trying to avoid any other factors (e.g. urban growth) might have affected the vegetation cover. The five areas show similar changes in land cover classes but with different percentages (Table 8.1). According to the results, the CF class is decreased in all areas (both inland and coastal), however, the percentage decrease in Areas 1 and 2 which are located near the coast area are higher compared with the other three areas. This is likely due to the salinisation of groundwater in the coastal area. The highest change in the PLNV class was observed in Areas 3 and 5, which is because the PLNV is largely located in those areas. As described previously in section 5.2 the that groundwater changes (quantity and quality) are might the main reason of the vegetation change particularly those which are sensitive to these changes (orange trees)

Table 8.1. Percentage (%) changes in vegetation classes in the areas of interest from 1988-2000.

Class	Area 1	Area 2	Area 3	Area 4	Area 5
OT	-3	-3	5	-9	-3
CF	-15	-13	-10	-7	-11
AC	16	10	7	7	7
PLNV	-7	-7	-14	-10	-9

There are two different impacts that the effect of groundwater changes can have on the vegetation cover in the area (questionnaire). Firstly a direct impact, which is related to the water availability. Secondly, an indirect impact, which is related to other effects that lowering can have on groundwater e.g. water quality (salinisation) particularly in the coastal area, the cost of water supply (i.e. having to re-dig and/or dig new wells) and plant disease when the environment gets dry (questionnaire).

8.3. Special relationship between groundwater change and land cover change

In some parts of the Jeffara region the water level has declined over 1 m year^{-1} over the last four decades (Abufayed and El-Ghuel, 2001). The changes are not uniform across the whole region, however, with some variation between the inland area and coastal areas, for example. In addition, changes in the water level in the study area have also affected the water quality. For example, in inland areas water quality can also be affected by water lowering (section 5.2) as the water becomes hotter and contains increased sulphur dioxide as the situation in Area 3 and 4 (questionnaire).

To exemplify the relationships between groundwater changes and vegetation cover (agricultural), three areas of interest were chosen with different properties (quality and amount of change). Area 1 near in the coast (quality) and Areas 3 and 5 are inland areas and show groundwater decline. Table 8.2 shows the area of each class of interest in 1988, 1992, 1996 and 2000 together with groundwater level determined by measuring the depth of the water table in the piezometric wells located in each area. Generally, the change in groundwater level is dependent on the location in the study area. For example, in coastal areas (Area 1) the change in groundwater level is small compared with the inland areas (Areas 3 and 5), since sea water fills the pore spaces after fresh groundwater levels fall (El Fleet and Baird, 2001, questionnaire survey), which maintains the groundwater at a similar level but poorer in quality.

Table 8.2. Groundwater level and the area (pixel) of each of land cover classes of interest in Areas 1, 3, and 5 from 1988, 1992, 1996 and 2000.

	Date	GWL (m)	OT	CF	AC	PLNV
Area 1	1988	39.03	25008	17541	4168	9041
	1992	38.59	29194	12593	3416	8138
	1996	38.08	27287	13644	2025	10405
	2000	37.42	22889	7914	14300	5292
Area 3	1988	18.80	19278	7735	7333	26743
	1992	22.00	23320	7570	7189	20424
	1996	29.75	29639	5844	3860	16981
	2000	35.30	21708	2314	10899	15841
Area 5	1988	75.70	35363	13530	4720	8175
	1992	106.34	34405	11511	1763	8887
	1996	126.61	32019	9494	1841	11120
	2000	143.98	32573	5945	9151	3979

Table 8.2 reveals a positive relationship between groundwater level changes and the area of the vegetation classes, and suggesting that when the groundwater decreases the vegetation classes also decrease (except for the annual crops class for reasons referred previously). For example, citrus fruit is sensitive to changes in groundwater quantity/quality (farmers' comments). Three specific areas were chosen to analyse the

spatial variability in groundwater changes and the changes in the vegetation cover. Area 3 and Area 5 are located in the interior of the study area (inland area), and Area 1 is located in the coastal area. The citrus fruit class (i.e. orange trees) is one of the sensitive trees to the groundwater changes quantity / quality (questionnaire survey). Therefore, the relationship between the change in the CF class and groundwater level changes in the three areas of interest were compared.

There is an overall decrease in the CF class across the study area, Figures 8.2, 8.3 and 8.4 shows the relationship between the changes in the citrus fruit class and the groundwater changes in Areas 1, 3 and 5. Since the Y axis illustrates the area of CF class by pixel and the X axis illustrates the depth of groundwater under the surface. The nature of change in the groundwater is different from one area to another (i.e. decrease/increase) and the magnitude is also different, therefore the scale of the X axis is different for each area, Figure 8.2 (Area 1) shows that there is relationship between the change in CF class and the groundwater changes. Therefore, the decrease in CF class as groundwater changes is potentially therefore a good indicator for future citrus production (Shrivastava and Gebelein, 2006).

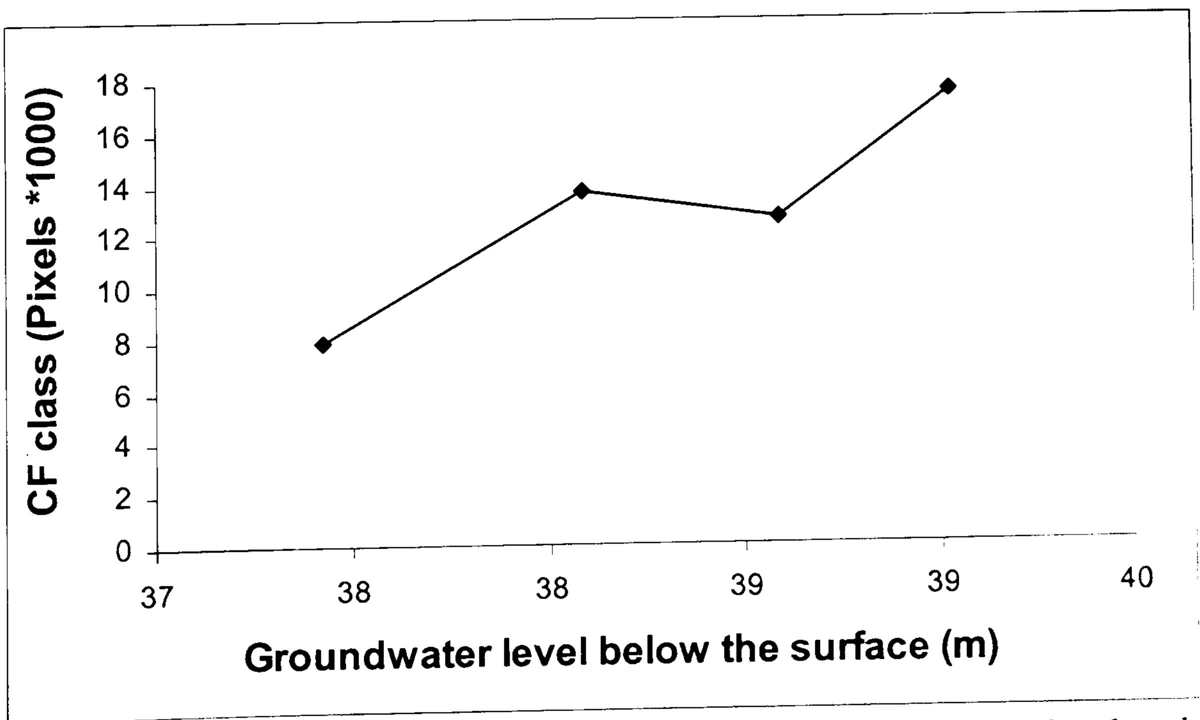

Figure. 8.2. The relationship between changes in groundwater level and the number of pixels of CF class in Area 1.

Inland areas show a periodical positive linear relationship between the change in the area of CF class and groundwater level changes. Figure 8.3 and 8.4 and Table 8.2 show in each of the periods 1988-1992, 1992-1996, 1996-2000, a fall of groundwater level is accompanied by a decrease in the area of CF class.

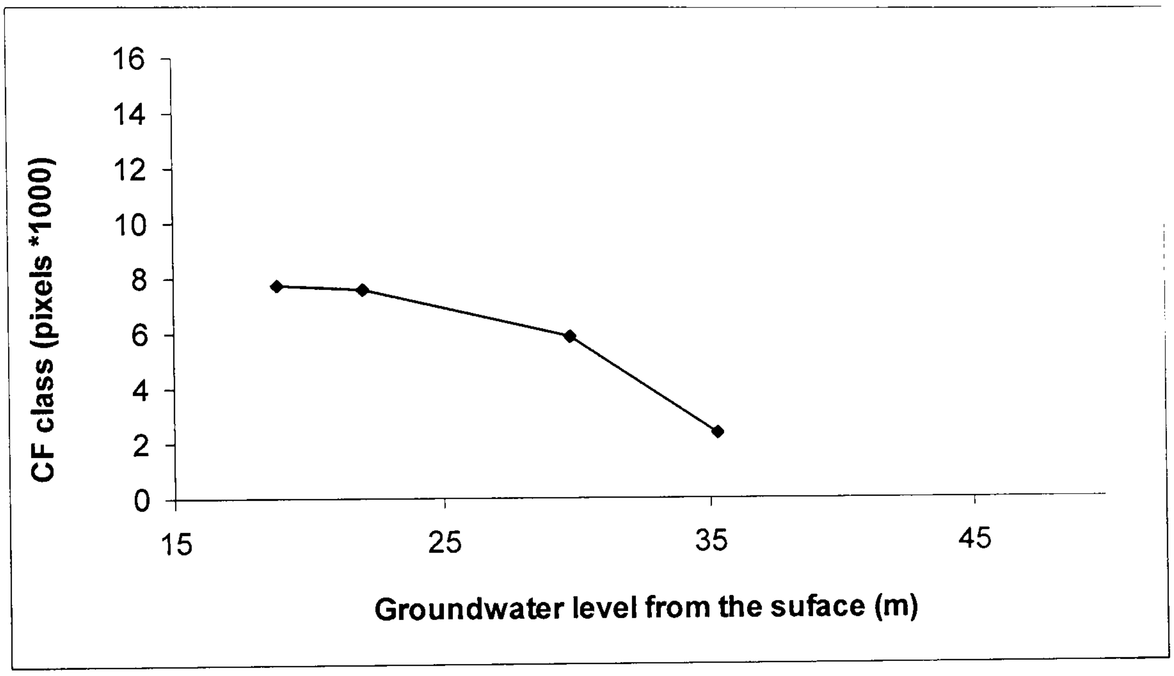

Figure. 8.3. The relationship between the changes in the groundwater level and the number of pixels of CF class in Area 3.

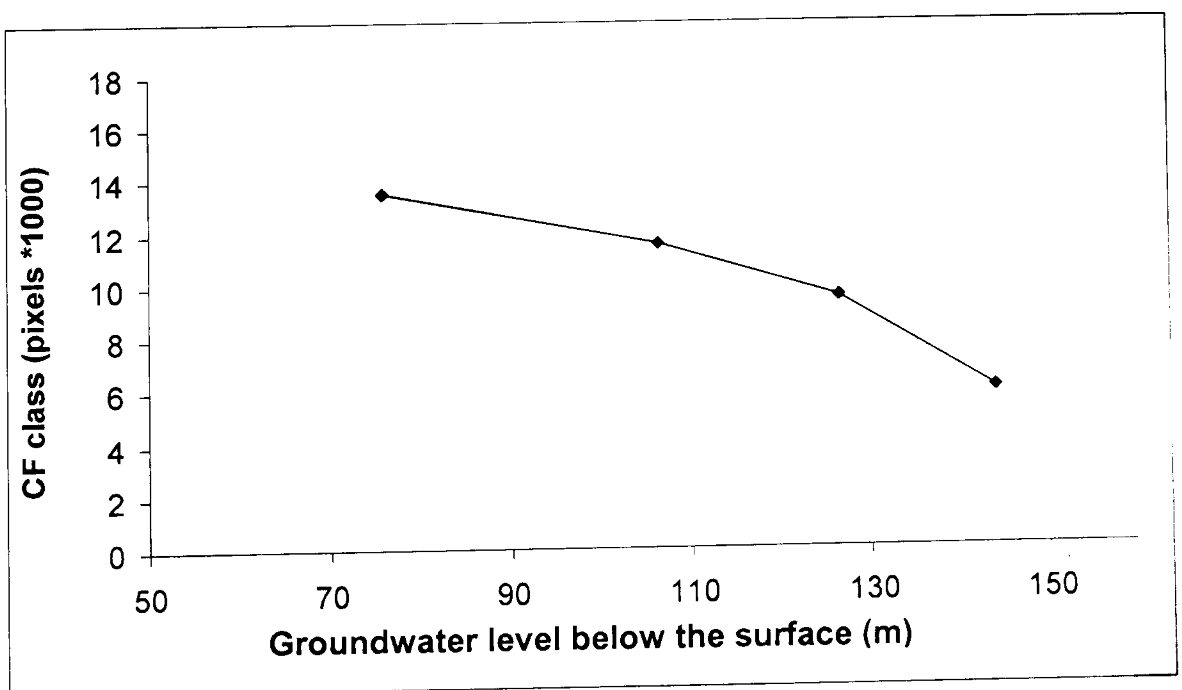

Figure. 8.4. The relationship between changes in groundwater level and the number of pixels of CF class in Area 5.

As the relationship between the groundwater and the natural vegetation in the arid and semiarid region (Elmore *et al.*, 2003; Munoz-Reinoso, 2001; Xu *et al.*, 2007), the importance of the groundwater for the vegetation cover (Le Maitre *et al.*, 1999) and the impact of the groundwater lowering on the vegetation cover (Brooks *et al.*, 2001). In the study area there are clear relationship between the changes in the groundwater level and the changes in the natural vegetation class (Figure 8.5) with natural vegetation decreasing as groundwater level decline (Xu *et al.*, 2007; Munoz-Reinoso, 2001). This particular class is directly affected by groundwater availability as it is not used for any other land use.

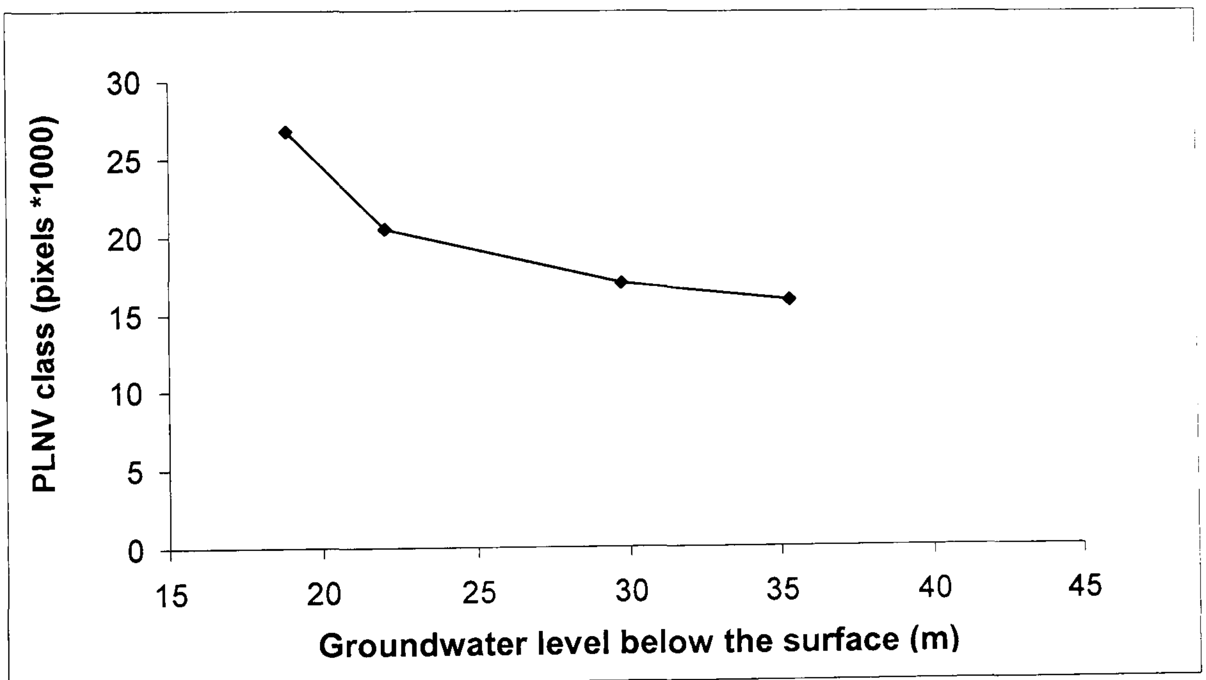

Figure. 8.5. The relationship between changes in groundwater level and the number of pixels of PLNV class in Area 3.

The aquifers in the study area are not recharged by precipitation, and with no surface water (e.g. rivers), it is unlikely that the change in land cover will have any significant impact on groundwater recharge. The remote sensing observations and the questionnaire survey suggest that in the Jeffara Plain the vegetation cover (particularly agricultural activities) is affected predominately by the groundwater changes (availability and quality) and reduces the area of trees and crops under cultivation which are sensitive to change in the groundwater (e.g. especially citrus trees). Ultimately, with little or no recharge to the aquifers this could lead to serious environmental degradation (desertification) in the area. The Great Man Made River project is planned to divert water from southern Libya to the coastal cities to be used for agriculture. A part of this water is likely help to recharge the shortage of groundwater in the area and so ameliorate the effects observed thus far. If the GMMR project does not address the ground water problems (quality and quantity) noted then the pattern of land cover changes observed in the area are likely to continue and lead to problems of environmental degradation and desertification.

8.4. Summary and limitations

It has been determined that the change in vegetation cover is related to the change in groundwater availability and quality due to the lowering of the groundwater level in the area. Thus, the use of high spatial resolution data which used to identify and assess the changes in land cover (vegetation cover) has been validated and offered realistic results, which occurred due to changes in groundwater quantity and quality and were compatible and confirmed by the questionnaire and the informal interviews with the farmers. There are relationships between the amount of change in groundwater (availability and quality) and amount of change in vegetation land cover (questionnaire survey). This, however, is not a straightforward relationship and so to build statistically valid model for further research a larger number of sites and images are required for analysis and prediction of future trends. There is a limitation in the remote sensing results, as the error and the misclassification of the classes.

The research has been undertaken using two different methods to identify vegetation land cover changes, and then related to the groundwater changes (quantity / quality) by using questionnaire survey. Both the statistical (ML) and the neural network approaches

(ANN) have limitations of accuracy. The accuracy of the classification depends on many issues; (i) Data availability; (ii) Quality of the data to be classified; (iii) The validity of the data used as reference and the gap in time between the classified images and the validation data; (iv) The similarity of some land cover classes making them difficult to separate. Whilst the accuracy of the classification was generally between 67% and 76%, this was based upon a pragmatic rather than an ideal approach to accuracy assessment, relying on only a limited set of available validation data. In addition, the ML algorithm is also prone to a number of influences that can affect the accuracy of the outputs, e.g. mixed pixel and atmospheric effects (Foody, 2002).

Also, as the study area is typically composed of small fields with a high degree of spectral similarity, this made it difficult to distinguish the spectral boundaries between the classes, and hence led to errors from misclassification (Powell *et al.*, 2004), seen particularly in the results of the OT, CF and AC classes. Due to the pixel size of Landsat images (30 m × 30 m) and the spaces between the lines of trees (5-20 m) in which different kinds of vegetation are present, misclassification as one of the issues which make reductions in the accuracy results. Further limitations are the mismatch in the geometric correction of images and GPS data errors, since the perfect registration of multitemporal images is impossible as there is residual error in rectification models (Labovitz and Marvin 1986) and the misregistration has effects which reduce the accuracy of the classified images. Finally, the results of the questionnaire survey depend on the responses which assuming is truthful and realistic.

CHAPTER NINE

Conclusions

9.1. Summary

Changes in groundwater level are important and can impact on features on the Earth's surface which are dependent on groundwater, such as vegetation and urban distribution. Over the last few decades, groundwater lowering has been reported in the northwest of Libya and this lowering has affected agricultural activities (vegetation cover) in the region. The questionnaire survey made an attempt to elicit information related to groundwater changes during the last 20 years and also the impact on agricultural activities linked to those change and the relationships between them.

Questionnaire surveys are particularly useful for eliciting people's attitudes and opinions about a subject (Malafferty, 2003). It was helpful to recognize the change in land cover (particularly agricultural activities) linked to groundwater changes in the study area. The respondents to the questionnaire survey have provided important information about groundwater changes in the last 20 years, and the relationship of these changes with agricultural activities in the region. Forty-nine % of the respondents believed the there has been change in the pattern of vegetation in the last 20 years with 74% suggesting that these changes are related to changes of groundwater level. All indicators from field observations, literature and questionnaire surveys suggest that there is change in the vegetation cover (e.g. crops / trees grown in the area), and there is a strong relationship between these changes and the changes in the groundwater level.

The supervised classification was applied to classify the Landsat TM5 images of 1988, 1992, 1996 and 2000 to identify land cover changes (vegetation cover) following Hall *et al.* (1991), Xu and Young (1990), and Yuan *et al.* (2005). The Maximum Likelihood classification, one of the traditional parametric approaches widely applied for supervised classification of remotely sensed data (Richards, 1993; McIver and Friedl, 2002), has been used in this project. The results were compatible and confirmed by the questionnaire survey and the informal interviews with the farmers.

Several studies have noted that the results of image classification using ANNs are considerably better than results from statistical parametric classifiers such as ML (Berberoglu *et al.,* 2000; Chiuderi, 1999). Therefore, multi-layer perceptron (MLP) trained by the back-propagation algorithm (Lee *et al.*, 1990; Lippmann, 1989; McClelland *et al.,* 1989) was used to classify the Landsat TM images to identify changes in the land cover. The ANN classifier was able to classify land cover with a high accuracy using Landsat TM imagery, therefore agreeing with observations from a number of other studies (e.g. Carpenter *et al.,* 1999; Han *et al.,* 2003; Ritter and Hepner., 1990).

Results from the ML and ANN were similar and showed that the changes in vegetation cover were linked to groundwater level changes. In addition, remote sensing is useful in being able to locate changes at the farm scale and provides results with high accuracy. The results show both increases and decreases in land cover classes. The classification of land cover was not intended to produce a map of all classes rather than to identify changes in vegetation classes which might be related to changes in groundwater level. The most interesting classes in the area are OT, CF, AC and PLNV, four classes that are responsive to changes in groundwater level as their only source of water supply for irrigation (Questionnaire survey).

9.2. Key findings and conclusion

The aim of this study was to identify the change in the vegetation cover (particularly agricultural related land cover) with remotely sensed data and identify the nature of the relationship between these changes and groundwater lowering in the Jeffara Plain through a questionnaire survey.

The first objective was to: *To identify the surface effects of groundwater lowering with respect to land use / cover changes (particularly agricultural activities) in the study area from field observations, literature and questionnaire surveys.*

The questionnaire survey responses suggested that there had been a change in the vegetation cover in the area, either in the types of crops/trees grown (agricultural activities) or in the natural vegetation where there is a direct relationship to the groundwater.

The second objective was *to identify and test appropriate remote sensing methods to detect and monitor land cover changes over time, including a comparison of image classification results from two different classification methods.*

The ML and ANN methods both provided realistic and comparable results for the vegetation cover changes during the period from 1988 to 2000, with acceptable classification accuracy for semi arid areas. The overall classification accuracy of the ML method varied between 67% and 76%, while the overall classification accuracy using the ANN method was 90% to 93% for all images.

To establish the relationship between groundwater changes and the changes in the land cover/use classes (particularly agricultural activities) observed from remote sensing in the study area compared with the literature and questionnaire surveys responses.

The changes determined in the vegetation classes from both classification methods (ML and ANN) are sensible and correspond well to the field observation and the questionnaire survey responses, indicating that groundwater change is the main driver for land cover change within the region. Spatially, increased changes in land cover were noted along the coast (e.g. CF class) which suffered from increasing salinity rather than groundwater lowering. Thus both groundwater availability and quality were directly linked with changing land cover.

To describe the pattern of land cover/use change in the study area from 1988-2000 and comment upon future implications of groundwater change and its associated impacts upon land cover/use in the region.

The pattern vegetation change in the area showed large decreases in the area of citrus fruit cultivation, as well as other fruit trees. To maximise water efficiency then more use was made of growing crops between trees, thus increasing landscape heterogeneity (with associated implications for remote sensing). There was an overall decline in the extent of semi-natural vegetation, possibly indicating increased landscape degradation (desertification) through groundwater availability, although this was not investigated specifically. Assuming that groundwater exploitation continues in a similar fashion then the above patterns of change indicate that groundwater lowering in the future will be a serious cause of the land degradation in the area and may severely impact biodiversity of the area.

9.3. Future work

The observed relationships between the change in groundwater level and land cover suggest that it might be possible to use these as inputs to a predictive model of landscape change. A key suggestion is for a database for all information about the factors which might contribute to change in land cover (e.g. groundwater quantity and quality, urban growth, economic, social) to be created. This could then incorporated into GIS models that are applied the environmental systems to predict and simulate future conditions over space and time (Skidmore, 2002). Hydrological models such Yeh *et al.* (2008) have been developed to predict groundwater recharge change, and not much has been done to predict its surface effects. Therefore, a GIS model for predicting the future situation of the vegetation cover could be created using the relationship between the change in vegetation cover and the causes of change, using the rule "the decrease of groundwater level is followed by the decrease in the area of the citrus fruit" for example. An example of such a model is presented here as a conceptual model for predicting future land cover changes in the Jeffara plain via the relationship between groundwater level changes and changes of vegetation cover classes (Figure 9.1).

This model could be developed to provide information to decision makers for water management and control of agricultural activities (type of trees/crops growth) in the region. As a key input to the model, remote sensing images are used to identify the changes in vegetation classes which might be affected by changes in the groundwater level. In addition, groundwater data (level) and other ancillary information (e.g. water quality data, various maps, and questionnaire replies) which describe factors that might impact on vegetation cover (agricultural activities), can also help in identifying the important classes in the area. Secondly, the data from the first step (remote sensing) are integrated to build a database containing all information about the features in the area.

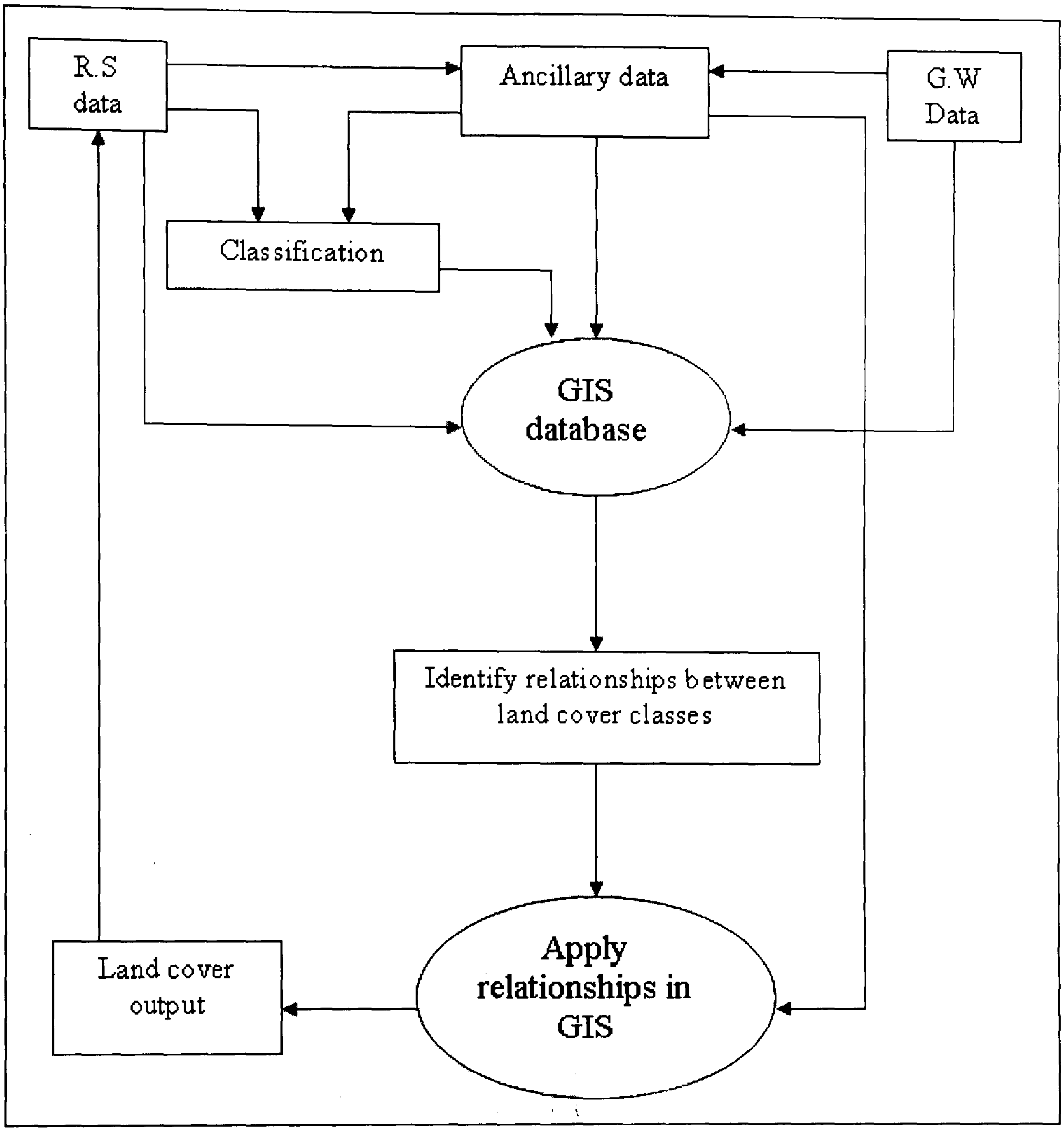

Figure 9.1. Simplified conceptual model of land cover change prediction.

As the final part of this step the statistical relationships between the classes and the groundwater changes are identified. Finally, the vegetation cover in the future can be predicted in the region by applying the GIS model using the relationship between vegetation classes, groundwater changes and other factors which might affect vegetation cover.

Other further work should examine:

- The derivation of training data for input to ANN classification algorithms.

- The effect of groundwater changes on indices of biodiversity in the region, particularly its effects on the semi natural vegetation.
- The use of high spatial resolution remotely sensed data to more effectively characterise the differences in cropping patterns and land cover change in an increasingly heterogeneous landscape.

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Appendix (I)

Groundwater data were provided by the Libyan General Water Authority (LGWA), collected by measuring the groundwater level from a number of piezometric wells situated in the region

Piezometer N°: **1006**

Location : Qasr bin ghashir Sheet N°: 1990 / 3

Coordinates : X: 32955 Y:361850

Elevation (m) : 69.02 Refrence point (m) : 0.70

Depth (m) : 130.00 Aquifer :Plio-Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
22/01/1980	-61.66	20/10/1985	-81.39
26/05/1980	-65.44	03/12/1985	-80.61
07/07/1980	-69.12	31/12/1985	-73.21
10/09/1980	-72.08	13/02/1986	-72.26
12/11/1980	-68.05	15/07/1986	-89.71
14/12/1980	-63.38	04/08/1986	-90.95
15/02/1981	-60.22	27/08/1986	-91.20
15/03/1981	-60.83	06/01/1988	-74.54
18/04/1981	-63.51	16/04/1989	-77.52
17/05/1981	-64.60	04/06/1989	-85.84
14/06/1981	-68.86	18/11/1989	-87.82
18/07/1981	-72.65	23/01/1990	-76.73
15/09/1981	-74.53	02/01/1993	-86.00
22/11/1981	-70.69	01/01/1994	-93.60
20/12/1981	-66.91	27/11/1994	-101.66
18/05/1982	-67.36	31/10/1995	-101.48
23/06/1982	-72.90	13/06/1996	-101.91
22/08/1982	-77.23	28/12/1997	-94.80
20/09/1982	-77.79	14/06/1998	-96.19
19/10/1982	-77.41	20/08/1998	-96.37
16/11/1982	-71.34	30/09/1998	-96.18
07/02/1983	-63.73	03/12/1998	-96.67
15/03/1983	-64.33	27/01/1999	-95.98
21/06/1983	-75.14	24/02/1999	-93.83
01/02/1984	-65.04	17/03/1999	-93.91
29/04/1984	-70.91	06/06/1999	-95.10
30/07/1984	-79.58	09/09/1999	-96.54
11/09/1984	-81.21	25/12/1999	-97.49
21/01/1985	-66.59	23/03/2000	-97.00
04/03/1985	-67.98	20/06/2000	-97.42
29/04/1985	-71.74	17/09/2000	-97.84
04/07/1985	-80.54	10/12/2000	-97.82
31/07/1985	-81.25		
15/09/1985	-82.31		

Piezometer N°: 1051

Location : Tripoli Sheet N°: 1990 / 4
Coordinates : X: 32690 Y: 363260
Elevation (m) : 42.39 Refrence point (m) : 0.40
Depth (m) : 50.00 Aquifer : Mio-Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
17/12/1978	-40.09	13/10/1985	-43.12
28/02/1979	-40.24	28/11/1985	-43.08
17/11/1979	-40.54	26/12/1985	-42.98
16/01/1980	-40.61	19/02/1986	-42.96
27/07/1980	-41.17	20/07/1986	-43.30
14/09/1980	-41.29	09/08/1986	-43.33
13/10/1980	-41.37	03/09/1986	-43.37
16/10/1980	-41.43	04/11/1986	-43.28
15/12/1980	-41.41	06/01/1988	-43.04
17/01/1981	-41.38	18/04/1989	-42.86
16/02/1981	-41.26	31/05/1989	-43.02
21/03/1981	-41.32	04/11/1989	-43.09
20/04/1981	-41.48	18/01/1990	-43.05
18/05/1981	-41.58	31/03/1990	-43.08
20/06/1981	-41.65	04/06/1990	-43.14
20/07/1981	-41.74	11/08/1990	-43.35
17/09/1981	-41.89	27/11/1994	-43.33
23/11/1981	-41.92	31/10/1995	-43.39
21/12/1981	-41.91	13/06/1996	-43.4
17/03/1982	-41.98	28/12/1997	-43.2
04/05/1982	-41.81	14/06/1998	-43.51
19/09/1982	-42.30	03/12/1998	-43.63
17/10/1982	-43.32	06/06/1999	-43.69
15/11/1982	-42.27	25/12/1999	-43.75
19/12/1982	-42.20	23/03/2000	-43.81
07/03/1983	-42.12		
05/07/1983	-42.48		
25/01/1984	-42.63		
22/04/1984	-42.73		
21/07/1984	-42.97		
28/08/1984	-43.03		
11/12/1984	-42.85		
14/01/1985	-42.77		
23/02/1985	-42.73		
22/04/1985	-42.85		
03/06/1985	-42.13		
25/07/1985	-43.00		
08/09/1985	-43.05		

Piezometer N°: **1057**

Location : Al Mayah — Sheet N°: 1890 / 1

Coordinates : X: 29560 — Y:363055

Elevation (m) : 44 — Refrence point (m) : 0.50

Depth (m) : 60.00 — Aquifer : Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
27/01/1980	-37.70	03/07/1985	-39.03
22/07/1980	-38.80	28/07/1985	-37.72
06/09/1980	-38.67	12/09/1985	-36.91
06/10/1980	-38.02	16/10/1985	-36.88
09/11/1980	-36.21	01/12/1985	-36.79
09/12/1980	-37.17	29/12/1985	-36.73
07/01/1981	-36.00	22/02/1986	-36.58
08/02/1981	-35.89	21/07/1986	-38.58
07/03/1981	-37.99	10/08/1986	-38.36
13/04/1981	-37.80	06/09/1986	-38.73
11/05/1981	-36.92	08/06/1989	-39.32
08/06/1981	-37.80	08/11/1989	-39.94
12/07/1981	-36.58	11/02/1990	-39.20
08/09/1981	-36.40	31/05/1990	-39.77
16/11/1981	-36.24	01/12/1993	-37.40
13/12/1981	-36.12	27/12/1993	-38.81
18/01/1982	-36.03	30/11/1994	-38.08
15/03/1982	-35.99	13/03/1999	-37.86
05/05/1982	-36.75	13/06/1999	-37.98
07/06/1982	-37.44	05/09/1999	-38.23
17/08/1982	-36.40	30/12/1999	-37.42
07/09/1982	-36.41	14/03/2001	-38.22
05/10/1982	-38.15		
02/11/1982	-36.44		
08/12/1982	-36.30		
27/02/1983	-36.08		
06/07/1983	-36.30		
28/01/1984	-37.83		
23/04/1984	-38.21		
22/07/1984	-38.35		
29/08/1984	-38.85		
15/01/1985	-36.53		
24/02/1985	-36.61		
23/04/1985	-36.73		

Piezometer N°: **1134**

Location : Bir trfas Sheet N°: 1890 / 2

Coordinates : X: 28910 Y:361850

Elevation (m) : 80.68 Refrence point (m) : 0.00

Depth (m) : 600.00 Aquifer : Lower Miocene

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
02/08/1980	-9.27	11/01/1986	-13.68
02/09/1980	-9.32	27/01/1986	-13.65
28/10/1980	-9.32	22/04/1986	-14.22
25/11/1980	-9.38	06/07/1986	-16.33
22/12/1980	-9.35	30/07/1986	-17.87
24/01/1981	-9.31	24/08/1986	-18.80
22/02/1981	-9.31	18/06/1989	-18.37
26/03/1981	-9.42	05/02/1990	-19.16
25/04/1981	-9.48	28/06/1990	-19.44
27/05/1981	-9.58	01/12/1993	-22.00
27/06/1981	-9.59	28/12/1993	-24.61
11/08/1981	-9.68	29/12/1994	-26.37
20/09/1981	-9.76	28/11/1995	-28.53
24/10/1981	-9.82	07/08/1996	-29.75
29/11/1981	-9.84	30/12/1997	-31.16
02/01/1982	-9.95	16/08/1998	-31.96
14/03/1982	-9.97	20/09/1998	-32.15
23/05/1982	-10.08	06/12/1998	-32.61
25/07/1982	-10.22	30/01/1999	-32.79
31/08/1982	-10.50	28/02/1999	-32.91
25/09/1982	-10.63	13/03/1999	-32.94
24/10/1982	-10.76	13/06/1999	-33.24
21/11/1982	-10.83	05/09/1999	-33.74
09/02/1983	-11.06	22/12/1999	-34.47
19/03/1983	-11.33	26/03/2000	-34.80
04/07/1983	-11.50	27/04/2000	-34.88
29/02/1984	-12.07	28/06/2000	-35.30
06/05/1984	-12.19	24/09/2000	-36.11
04/08/1984	-12.39	17/12/2000	-36.74
19/12/1984	-12.59		
05/02/1985	-12.55		
26/03/1985	-12.66		
19/05/1985	-12.75		
09/07/1985	-12.94		
05/08/1985	-13.00		
21/09/1985	-13.24		
24/10/1985	-13.90		
07/12/1985	-13.74		

Piezometer N°: **1172**

Location :	Gasr Bin Ghashir	Sheet N°: 1990 / 3	
Coordinates :	X: 32845	Y:361385	
Elevation (m) :	85	Refrence point (m) :	0.76
Depth (m) :	400.00	Aquifer : Lower Miocene	

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
22/01/1980	-45.47	03/12/1985	-71.96
02/07/1980	-48.15	31/12/1985	-67.88
10/09/1980	-49.98	13/02/1986	-67.09
12/10/1980	-50.05	15/07/1986	-78.32
12/11/1980	-48.87	04/08/1986	-79.54
14/12/1980	-47.95	27/08/1986	-80.38
13/01/1981	-46.85	06/01/1988	-75.70
15/02/1981	-45.90	16/04/1989	-82.46
15/03/1981	-45.43	04/06/1989	-89.17
18/04/1981	-46.16	18/11/1989	-94.10
17/05/1981	-46.77	23/01/1990	-83.12
21/06/1981	-48.29	01/01/1994	-106.34
18/07/1981	-49.39	25/12/1994	-113.72
15/09/1981	-50.99	31/12/1995	-116.15
22/11/1981	-51.01	05/06/1996	-122.03
20/12/1981	-50.07	13/07/1996	-126.61
27/02/1982	-48.87	28/12/1997	-116.28
18/05/1982	-51.14	08/06/1998	-134.80
23/06/1982	-52.26	20/08/1998	-144.07
22/08/1982	-54.68	30/09/1998	-144.46
20/09/1982	-55.45	03/12/1998	-130.55
19/10/1982	-55.58	28/01/1999	-118.83
16/11/1982	-53.85	27/02/1999	-110.62
07/02/1983	-49.94	17/03/1999	-119.05
15/03/1983	-50.76	02/05/1999	-124.47
21/06/1983	-56.62	05/06/1999	-140.63
01/02/1984	-55.75	12/08/1999	-149.52
29/04/1984	-59.15	09/09/1999	-150.33
30/07/1984	-67.13		
11/09/1984	-69.14		
21/01/1985	-61.28		
04/03/1985	-62.06		
29/04/1985	-65.60		
04/07/1985	-71.67		
31/07/1985	-73.05		
15/09/1985	-73.96		
20/10/1985	-72.93		

Piezometer N°: **1173**

Location : Gasr Bin Ghashir Sheet N°: 1990 / 3
Coordinates : X: 32843 Y:361385
Elevation (m) : 85 Refrence point (m) : 0.65
Depth (m) : 250.00 Aquifer :Miocene

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
13/12/1978	-42.24	31/07/1985	-74.48
13/02/1979	-42.74	20/10/1985	-74.00
11/10/1979	-46.97	31/12/1985	-67.98
08/11/1979	-46.95	13/02/1986	-67.61
22/01/1980	-45.71	15/07/1986	-79.43
02/07/1980	-48.59	04/08/1986	-80.89
26/08/1980	-50.18	06/01/1988	-76.05
10/09/1980	-50.38	16/04/1989	-83.39
12/10/1980	-50.54	04/06/1989	-90.30
12/11/1980	-49.18	23/01/1990	-83.16
14/02/1980	-48.19	31/07/1995	-74.48
13/01/1981	-47.05		
15/02/1981	-46.05		
15/03/1981	-45.60		
18/04/1981	-46.40		
17/05/1981	-47.07		
21/06/1981	-48.68		
18/07/1981	-49.79		
15/09/1981	-50.46		
22/11/1981	-51.39		
20/12/1981	-50.41		
27/02/1982	-50.36		
18/05/1982	-50.80		
23/06/1982	-52.78		
22/08/1982	-55.21		
20/09/1982	-55.96		
19/10/1982	-56.07		
16/11/1982	-54.03		
07/02/1983	-50.02		
15/03/1983	-50.93		
21/06/1983	-57.15		
01/02/1984	-55.86		
29/04/1984	-57.35		
30/07/1984	-68.07		
11/09/1984	-70.34		
21/01/1985	-61.28		
04/03/1985	-62.25		

Piezometer N°: **1177**

Location : Tripoli Sheet N°: 1990 / 4

Coordinates : X: 32045 Y:363365

Elevation (m) : 25.14 Refrence point (m) : 0.70

Depth (m) : 204.00 Aquifer : Miocene

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
19/01/1980	-14.37	16/10/1985	-27.06
27/07/1980	-16.58	01/12/1985	-26.74
06/09/1980	-17.06	29/12/1985	-25.39
06/10/1980	-17.20	22/02/1986	-24.57
09/11/1980	-16.84	21/07/1986	-28.18
09/12/1980	-16.44	10/08/1986	-28.45
07/01/1981	-15.89	06/09/1986	-29.09
08/02/1981	-15.35	08/06/1989	-28.78
07/03/1981	-15.18	08/11/1989	-30.21
13/04/1981	-15.55	11/02/1990	-26.50
11/05/1981	-16.00	27/12/1993	-32.66
08/06/1981	-16.70	24/11/1994	-35.15
12/07/1981	-17.60	11/08/1996	-36.90
08/09/1981	-18.54	05/11/1996	-36.92
16/11/1981	-18.47	22/12/1997	-34.59
21/12/1981	-17.87	01/04/1998	-32.03
18/01/1982	-17.81	07/06/1998	-34.88
15/03/1982	-17.34	20/09/1998	-38.86
05/05/1982	-18.34	03/10/1998	-38.77
07/06/1982	-18.40	02/12/1998	-35.56
17/08/1982	-20.61	27/01/1999	-33.58
07/09/1982	-20.98	09/03/1999	-32.51
05/10/1982	-21.24	02/06/1999	-35.52
02/11/1982	-21.30	12/09/1999	-39.69
08/12/1982	-20.48	21/12/1999	-35.98
27/02/1983	-19.36	28/03/2000	-32.56
06/07/1983	-22.72	26/04/2000	-34.21
28/01/1984	-22.02	27/06/2000	-36.74
23/04/1984	-23.00	20/09/2000	-37.71
22/07/1984	-25.28	18/12/2000	-36.04
29/08/1984	-25.94		
15/01/1985	-23.80		
24/02/1985	-23.57		
23/04/1985	-24.39		
03/07/1985	-26.54		
28/07/1985	-27.08		
12/09/1985	-27.33		

Piezometer N°: **1178**

Location : As Sawani — Sheet N°: 1990 / 4

Coordinates : X: 32255 — Y:362845

Elevation (m) : 25.14 — Refrence point (m) : 0.35

Depth (m) : 170.00 — Aquifer : Miocene

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
16/01/1980	-47.76	28/05/1985	-55.90
08/07/1980	-47.76	24/07/1985	-56.21
18/08/1980	-49.12	16/08/1985	-53.61
06/09/1980	-49.22	07/09/1985	-56.40
04/10/1980	-49.29	12/10/1985	-56.00
04/11/1980	-49.03	26/11/1985	-55.88
07/12/1980	-48.90	25/12/1985	-55.44
05/01/1981	-48.77	28/01/1986	-55.42
04/02/1981	-48.74	23/04/1986	-56.41
03/03/1981	-49.03	07/07/1986	-57.17
11/04/1981	-49.72	02/08/1986	-57.37
05/05/1981	-49.82	25/08/1986	-57.29
03/06/1981	-50.15	06/06/1989	-59.85
05/07/1981	-50.77	15/01/1990	-59.58
12/09/1981	-50.82	09/07/1990	-61.68
18/10/1981	-51.18	25/12/1993	-64.69
14/11/1981	-48.34	28/11/1994	-66.70
08/12/1981	-50.40	30/10/1995	-68.00
11/01/1982	-50.84	14/07/1996	-70.44
20/03/1982	-50.68	22/12/1997	-69.02
02/05/1982	-51.15	11/08/1998	-73.63
01/06/1982	-51.68	27/09/1998	-73.25
01/08/1982	-52.68	13/12/1998	-70.08
04/09/1982	-52.65	01/02/1999	-68.48
04/10/1982	-52.63	28/02/1999	-68.80
01/11/1982	-52.10	14/03/1999	-69.27
01/12/1982	-51.81	09/06/1999	-74.87
22/02/1983	-51.95	11/09/1999	-73.99
27/03/1983	-52.25	26/12/1999	-70.26
17/07/1983	-54.02	28/03/2000	-70.29
23/01/1984	-53.20	30/04/2000	-72.15
15/04/1984	-53.82	21/06/2000	-75.87
18/07/1984	-55.56	19/09/2000	-76.10
26/08/1984	-55.79	13/12/2000	-76.08
12/01/1985	-54.54		
17/02/1985	-54.95		
16/04/1985	-53.63		

Piezometer N°: **1179**

Location : Al Krimiyah Sheet N°: 1990 / 4
Coordinates : X:32255 Y: 362845
Elevation (m) : Refrence point (m) : 0.51
Depth (m) : 60.00 Aquifer :Mio-Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
16/12/1978	-43.45	12/01/1985	-53.44
03/02/1979	-43.09	17/02/1985	-53.51
26/03/1979	-43.77	16/04/1985	-55.21
09/10/1979	-44.85	28/05/1985	-53.75
16/01/1980	-45.20	24/07/1985	-53.99
08/07/1980	-45.94	16/08/1985	-55.29
18/08/1980	-46.22	07/09/1985	-54.23
06/09/1980	-46.33	12/10/1985	-54.37
04/10/1980	-46.51	26/11/1985	-54.52
04/11/1980	-46.68	25/12/1985	-54.64
07/12/1980	-46.83	28/01/1986	-54.75
05/01/1981	-46.93	23/04/1986	-55.00
04/02/1981	-47.00	07/07/1986	-55.32
03/03/1981	-47.09	02/08/1986	-55.45
11/04/1981	-47.20	27/08/1986	-55.60
05/05/1981	-47.30	06/01/1988	-55.80
03/06/1981	-47.44	16/04/1989	-56.00
05/07/1981	-47.60	04/06/1989	-55.95
12/09/1981	-47.98	18/11/1989	-56.12
18/10/1981	-48.20	23/01/1990	-56.30
14/11/1981	-50.69	02/01/1993	-56.35
08/12/1981	-48.42	01/01/1994	-56.80
11/01/1982	-48.55	27/11/1994	-56.98
20/03/1982	-48.76	31/10/1995	-56.50
02/05/1982	-48.87	13/06/1996	-56.70
01/06/1982	-49.01	28/12/1997	-56.90
01/08/1982	-49.48	14/06/1998	-56.95
04/09/1982	-49.60	03/12/1998	-57.29
04/10/1982	-49.86	27/01/1999	-57.40
01/11/1982	-50.00	06/06/1999	-57.55
01/12/1982	-50.16	25/12/1999	-57.20
22/02/1983	-50.36	23/03/2000	-57.25
27/03/1983	-50.44		
17/07/1983	-50.99		
23/01/1984	-51.91		
15/04/1984	-52.08		
18/07/1984	-52.57		

Piezometer N°: **1274**

Location : Tripoli Sheet N°:1990 / 4

Coordinates : X:32540 Y:363175

Elevation (m) : 45.91 Refrence point (m) : 0.45

Depth (m) : 79.00 Aquifer : Mio-Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
16/12/1978	-49.83	23/02/1985	-48.13
03/02/1979	-49.84	22/04/1985	-49.09
01/03/1979	-47.83	03/06/1985	-49.13
26/03/1979	-49.73	25/07/1985	-49.17
09/10/1979	-50.16	08/09/1985	-49.21
15/01/1980	-50.51	13/10/1985	-49.18
07/07/1980	-50.63	28/11/1985	-49.19
18/08/1980	-50.70	26/12/1985	-49.21
14/09/1980	-50.72	19/02/1986	-49.23
13/10/1980	-50.91	20/07/1986	-49.44
16/11/1980	-50.93	09/08/1986	-49.49
15/12/1980	-50.96	03/09/1986	-49.58
17/01/1981	-51.03		
16/02/1981	-50.93		
21/03/1981	-50.94		
20/04/1981	-50.98		
18/05/1981	-50.92		
20/06/1981	-51.04		
20/07/1981	-50.00		
17/09/1981	-51.14		
23/11/1981	-51.29		
21/12/1981	-51.30		
17/03/1982	-51.20		
11/05/1982	-51.88		
22/06/1982	-51.06		
23/08/1982	-49.33		
19/09/1982	-50.54		
17/10/1982	-50.50		
15/11/1982	-50.48		
19/12/1982	-50.59		
07/03/1983	-50.47		
05/07/1983	-50.50		
25/01/1984	-50.69		
22/04/1984	-50.67		
21/07/1984	-49.15		
28/08/1984	-49.37		
11/12/1984	-49.20		

Piezometer N°: **1327**

Location : Ain Zarah Sheet N°:1990 / 4

Coordinates : X:33325 Y:363165

Elevation (m) : 34.43 Refrence point (m) : 0.35

Depth (m) : 93.00 Aquifer : Mio-Quaternary

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
06/06/1978	-26.59	04/07/1985	-36.49
28/02/1979	-26.80	31/07/1985	-36.76
13/10/1979	-28.73	15/09/1985	-36.63
22/01/1980	-28.21	20/10/1985	-35.18
26/05/1980	-29.68	03/12/1985	-35.35
03/07/1980	-30.33	31/12/1985	-34.23
31/07/1980	-30.76	13/02/1986	-34.35
10/09/1980	-31.14	15/07/1986	-37.27
12/10/1980	-31.12	04/08/1986	-37.41
12/11/1980	-30.50	27/08/1986	-37.44
14/12/1980	-29.85	01/06/1988	-34.07
13/01/1981	-29.22	04/06/1989	-36.24
15/02/1981	-28.84	17/01/1990	-34.60
15/03/1981	-29.15	31/03/1990	-35.95
18/04/1981	-29.92	04/06/1990	-37.47
17/05/1981	-30.58	11/08/1990	-38.90
21/06/1981	-31.64	01/01/1994	-38.53
15/09/1981	-32.34	24/11/1994	-41.04
22/11/1981	-31.39	30/10/1995	-40.42
20/12/1981	-31.04	13/07/1996	-43.04
18/05/1982	-32.58	29/12/1997	-38.31
23/06/1982	-33.67	20/08/1998	-43.45
22/08/1982	-34.39	03/10/1998	-43.35
20/09/1982	-34.36	02/12/1998	-40.24
19/10/1982	-34.47	27/01/1999	-38.23
16/11/1982	-33.10	09/03/1999	-38.12
07/02/1983	-31.39	02/06/1999	-39.22
05/03/1983	-32.10	12/09/1999	-43.80
21/06/1983	-34.72	21/12/1999	-39.44
01/02/1984	-32.49	28/03/2000	-38.19
29/04/1984	-34.25	26/04/2000	-40.16
30/07/1984	-36.01	27/06/2000	-43.00
11/09/1984	-36.37	21/09/2000	-43.47
21/01/1985	-33.06	18/12/2000	-40.87
04/03/1985	-33.65	15/04/2001	-39.19
29/04/1985	-34.95	14/06/2001	-39.98
04/03/1985	-33.65		

Piezometer N°: **1373**

Location :	Az zahra	Sheet N°:1890 / 2	
Coordinates :	X:29805	Y:361010	
Elevation (m) :	80	Refrence point (m) :	0.00
Depth (m) :	59.00	Aquifer : Quaternary	

Date of measurement	Depth to water level from reference point	Date of measurement	Depth to water level from reference point
18/12/1978	-24.90	28/07/1985	-31.22
31/03/1979	-25.18	12/09/1985	-31.36
29/11/1979	-26.01	16/10/1985	-31.40
19/01/1980	-25.95	01/12/1985	-31.37
02/08/1980	-26.74	29/12/1985	-31.18
02/09/1980	-26.85	22/02/1986	-30.98
06/10/1980	-26.93	21/07/1986	-31.79
09/11/1980	-27.00	10/08/1986	-31.88
09/12/1980	-26.80	06/09/1986	-31.94
07/01/1981	-26.65	08/06/1989	-32.96
08/02/1981	-26.57	02/06/1990	-42.88
07/03/1981	-26.53	27/12/1993	-37.21
13/04/1981	-26.82	30/11/1994	-38.02
11/05/1981	-27.01	11/08/1996	-39.39
08/06/1981	-27.14	30/12/1997	-40.51
12/07/1981	-27.29	16/08/1998	-41.15
08/09/1981	-27.51	20/09/1998	-41.27
16/11/1981	-27.61	06/12/1998	-41.43
13/12/1981	-27.55	30/01/1999	-41.21
18/01/1982	-27.66	28/02/1999	-41.12
15/03/1982	-27.49	13/03/1999	-41.12
05/05/1982	-28.58	13/06/1999	-41.55
07/06/1982	-28.21	05/09/1999	-42.05
17/08/1982	-28.71	22/12/1999	-42.30
07/09/1982	-28.84	26/03/2000	-42.25
05/10/1982	-29.03	22/04/2000	-42.39
02/11/1982	-29.14	17/12/2000	-43.31
08/12/1982	-29.00	14/03/2001	-43.27
27/02/1983	-28.90	16/06/2001	-43.31
06/07/1983	-29.64		
28/01/1984	-29.71		
23/04/1984	-30.01		
22/07/1984	-30.59		
29/08/1984	-30.76		
15/01/1985	-30.66		
24/02/1985	-30.63		
23/04/1985	-30.85		

Appendix (II-A): *Table shows the points in* ***area one***

NO	From the image		Name of place	How to get there	From the field		Photos No				Description
1	32 46 34.77 N	12 45 45.86 E	Bigening of Elzawia	بداية الزاويه/ شمال الطريق مسجد القدس							
2	32 47 09.57 N	12 47 15.20 E	West Jodaim school 1.5km	غرب مدرسة جودائم 1.5 كم							
3	32 47 24.38 N	12 47 53.75 E	West Jodaim school 200m	غرب مدرسة جودائم 200 م							
4	32 47 31.61 N	12 48 34.08 E	West-Elkashaf Farm	غرب غابة جودائم / المنتدى العائلي							
5	32 47 31.05 N	12 49 37.30 E	Elkashaf	غابة جودائم/ المدخل الرئسي يسار							REF
6	32 47 52.62 N	12 51 03.48 E	El Maya	قرب مزرعة الشقمان							
7	32 47 02.00 N	12 50 49.98 E	El Towbia	قرب مزرعةابوجعفر							
8	32 44 40.42 N	12 50 43.96 E	Elantilak SM cross section	مفترق سوق الانطلاقه							
9	32 46 42.61 N	12 47 34.06 E	Jodaim-Abo Sahmen Farm	جودائم / مزرعة ابوسهمين							
10	32 45 51.09 N	12 45 30.02 E	Bigening of Elzawia	بداية الزاويه/ قرب مسجد القدس							
11	32 44 43.81 N	12 45 33.24 E	Elzawia-elarawi RD	الزاوية العريوي /الزراعه							
12	32 46 02.88 N	12 46 44.46 E	Jodaim-South-jafra	جودائم جنوب الجعافره							
13	32 44 38.02 N	12 47 40.86 E	Elarawi cross	غرب مفترق العريوي							
14	32 47 07.90 N	12 48 24.64 E	Jodaim- near to the center	قبل محل الاصفر يمين المزرعة							REF

Appendix (II-A2): *The root mean square error (RMS) for the check points in Area for image 2000*

No	Image points		Field points		E (image) -E(field)	N(image) -N (field)	Easting RMS	Northing RMS
	Easting	Northing	Easting	Northing				
1	290480	3628707	290396	3628624	83	83	50 m	54 m
2	292810	3629705	292809	3629706	1	-1		
3	293808	3630205	293891	3630122	-83	83		
4	294890	3630122	294807	3630122	83	0		
5	296554	3630372	296471	3630372	83	0		
6	298801	3630038	298801	3630039	0	-1		
7	298718	3629373	298718	3629290	0	83		
8	298135	3625046	298135	3625046	0	0		
9	293309	3628874	293309	3628957	0	-83		
10	289980	3627376	290064	3627459	-83	-83		
11	290064	3625296	290064	3625296	0	0		
12	291978	3627709	291978	3627709	0	0		
13	293392	3625046	293392	3625046	0	0		
14	294640	3629623	294640	3629706	0	-83		

Appendix II-B1

UNIVERSITY OF DUNDEE

IMPACTS OF GROUNDWATER CHANGES ON AGRICULTURAL ACTIVITY IN NORTHWESTERN LIBYA (Jeffara Plain)

In Libya, groundwater is the main source of freshwater, and therefore it is important to study the results of changes to it. Groundwater is an essential source of surface water for irrigation in agriculture, and is also vital for various other activities such as drinking and industry, for example. A consequence of any impacts on groundwater level or quality is an obvious change in the surface environment. This project seeks to examine the relationships between changes in groundwater level and changes in agricultural activities.

This questionnaire aims to explore information about groundwater and the land cover properties from 1988 to the present day and the relationship between these, in the El-Jeffara Plain which is located in the northwest of Libya. The information you provide will only be used only for research purposes and all responses will be kept anonymous.

- **Area name:**..........................

- **Area number:**.......................

Questionnaire *(please tick in one box to answer the question)*

1. How would you describe the quantity of groundwater in the 1980's?

Shortage	Intermittent Supply	Sufficient	Not an issue	I don't know
☐	☐	☐	☐	☐

2. How have groundwater quantity levels been in the last five years?

Shortage	Intermittent Supply	Sufficient	Not an issue	I don't know
☐	☐	☐	☐	☐

3. How does the ground water quantity today compare to that in the 1980's?

Less water	Similar	More water	I don't know
☐	☐	☐	☐

4. What has been the groundwater quality over the last five years?

Very Poor	Poor	Good	Very good	Excellent
☐	☐	☐	☐	☐

5. What was the depth of the ground water level at the end of the 1980's?

25-50 m	50-100 m	100-200m	Over 200m	I don't know
☐	☐	☐	☐	☐

6. What was the depth of the ground water level in the year 2000?

25-50 m	50-100 m	100-200m	Over 200m	I don't know
☐	☐	☐	☐	☐

What is the depth of the ground water level now?

25-50 m	50-100 m	100-200m	Over 200m	I don't know
☐	☐	☐	☐	☐

8. Has there been any depletion of ground water levels in this region in the last 20 years?

Major change	No change	Some change	I don't know
☐	☐ *Go to question 11*	☐	☐

If yes please answer Question 9 and 10

9. What is the reason for the depletion of groundwater?

Intensive use	Less precipitation	I don't no	Other
☐	☐	☐	☐....*Specify*

....
....
....
...

10. Do you believe that there is a relationship between the lowering of groundwater and the intensive use of water in the past 20 years?

Yes	No	Sometimes	I don't know
☐	☐	☐	☐

11. Is groundwater the main source of water for use in agriculture in El-Jeffara region?

Yes	No	I don't know
☐	☐	☐

If not please mention the other sources.

- ....
- ....
- ....

12. What are the main types agricultural of crops and trees grown in El-Jeffara region?

Crops	Trees
•	• ....
•	• ....
•	• ....
•	• ....

13. Has the pattern and types of crops/trees grown in this area changed during the past 20 years?

Yes	No	I don't know
☐	☐ *Go to question 14*	☐

If yes please answer questions A and B

A. What is different?

....
....
......

B. Do you believe that this difference is related to the groundwater?

Yes	No	I don't know
☐	☐	☐

If No please state the reason

- ....
- ....
- ....

14. Does a change in ground water supply influence the type of crops and trees grown in this area?

Yes	No	I don't know
☐	☐	☐

Please give details

....
....
....

15. Do you have any other comments related to ground water levels or any other property over the past 20 years that you wish to make?

....
....
....
....
....
....
....

UNIVERSITY OF DUNDEE

تأثير التغير في مستوى المياه الجوفية على النشاطات الزرعية في شمال غرب ليبيا (منطقة سهل الجفاره)

تكون المياه الجوفية في ليبيا هي المصدر الرئيسي للمياه العذبة، ولهذا الغرض يكون من المهم جدا" دراسة النتائج المترتبة عن التغيرات فيها. المياه الجوفية تكون هي المصدر الاساسي والجوهري للمياه السطحية لأجل الري في الزراعة، ويكون كذلك الجزء الحيوي في العديد من النشاطات الاخرى مثل مياه الشرب والصناعة على سبيل المثال . نتيجة" لاي تغير في مستوى المياه الجوفية أو نوعيته يتبعه تغير في البيئة المحيطة بالسطح. هذا المشروع يبحث عن إختبار العلاقة بين التغيرات في مستوى المياه الجوفية والتغيرات في النشاطات الزراعية في المنطقة. الهدف من هذا الاستفتاء، التحري عن المعلومات المتعلقة بالمياه الجوفية وخصائص الغطاء الارضي والعلاق بينهما في الفترة الزمنية من سنة 1988 إلى الوقت الحاضر في منطقة سهل الجفارة والتي تقع في الشمال الغربي من ليبيا. المعلومات التي تعطى سوف تستعمل فقط لهدف البحث وكل الاجابات سوف تحفظ غير معروفة المصدر.

- أسم المنطقة :..............................
- رقم المنطقة : (   )

الاستـــبيان *"ضع علامة في مربع واحد لإجابة السؤال"*

1. كيف تصف كمية المياه الجوفية في عقد الثمانينات ؟

غير كافي ☐	متغير ☐	كافي ☐	غير مقلق ☐	لا أعرف ☐

2. كيف كان مستوى كمية المياه الجوفية خلال الخمس سنوات الاخيرة ؟

غير كافي ☐	متغير ☐	كافي ☐	غير مقلق ☐	لا أعرف ☐

3. كيف هي كمية المياه الجوفية اليوم مقارنة بفترة الثمانينات ؟

مياه أقل ☐	مياه أكثر ☐	مماثل ☐	لا أعرف ☐

4. كيف كانت المياه الجوفية من حيث الجودة خلال الخمس سنوات الاخيرة ؟

ممتازة ☐	جيدة جدا" ☐	جيدة ☐	رديئة ☐	رديئة جدا" ☐

5. كيف كان عمق مستوى المياه الجوفية في آخر الثمانينات ؟

25- 50 م ☐	50- 100 م ☐	100- 200 م ☐	اكثر من 200 م ☐	لا أعرف ☐

6. كيف كان عمق مستوى المياه الجوفية في سنة 2000 ؟

25- 50 م ☐	50- 100 م ☐	100- 200 م ☐	اكثر من 200 م ☐	لا أعرف ☐

7. كيف هو عمق مستوى المياه الجوفية في هذه الايام ؟

25- 50 م ☐	50- 100 م ☐	100- 200 م ☐	اكثر من 200 م ☐	لا أعرف ☐

8. هل هناك اي هبوط في مستوى المياه الجوفية في هذه المنطقة خلال العشرين سنة الاخيرة ؟

لا أعرف ☐	لا ☐ إذهب الى السؤال 11	نعم ☐

إذا كانت الإجابة بنعم من فضلك اجب على السؤال 9، 10

9. ما هو السبب الناتج عنه الهبوط في مستوى المياه الجوفية ؟

أسباب أخرى ☐ بإيضاح	لا أعرف ☐	قلة الامطار ☐	الإستعمال المفرط ☐

....
....
....

10. هل تعتقد ان هناك علاقة بين الهبوط في مستوى المياه الجوفية والاستخدام الزائد للمياه في العشرين سنة الاخيرة ؟

لا أعرف ☐	أحيانا" ☐	لا ☐	نعم ☐

11. هل تكون المياه الجوفية المصدر الرئيسي للمياه للاستعمال في الزراعة في منطقة سهل الجفارة ؟

لا أعرف ☐	لا ☐	نعم ☐

إذا الاجابة "لا" من فضلك اذكر المصادر الاخرى .

- ....
- ....
- ....

12. ماهي انواع الزراعة الرئيسية من المحاصيل والاشجار التي تنمو في منطقة سهل الجفارة ؟

الاشجار	المحاصيل
•	• ....
•	• ....
•	• ....
•	• ....

13. هل أنواع ونماذج المحاصيل التي تزرع بالمنطقة تغيرت خلال العشرين سنة الماضية ؟

لا أعرف ☐	لا ☐ إذهب الى السؤال 16	نعم ☐

إذا كانت الإجابة بنعم من فضلك اجب على السؤال أ ، ب

أ. ما ذا يكون الاختلاف ؟

نعم	لا	لا أعرف
☐	☐ إذهب الى السؤال 11	☐

إذا كانت الإجابة بنعم من فضلك اجب على السؤال 9، 10

9. ما هو السبب الناتج عنه الهبوط في مستوى المياه الجوفية ؟

الاستعمال المفرط	قلة الامطار	لا أعرف	أسباب أخرى
☐	☐	☐	☐ *بإيضاح*

....
....
....

10. هل تعتقد ان هناك علاقة بين الهبوط في مستوى المياه الجوفية والاستخدام الزائد للمياه في العشرين سنة الاخيرة ؟

نعم	لا	أحيانا"	لا أعرف
☐	☐	☐	☐

11. هل تكون المياه الجوفية المصدر الرئيسي للمياه للاستعمال في الزراعة في منطقة سهل الجفارة ؟

نعم	لا	لا أعرف
☐	☐	☐

إذا الاجابة "لا" من فضلك اذكر المصادر الاخرى .

- ....
- ....
- ....

12. ماهي انواع الزراعة الرئيسية من المحاصيل والاشجار التي تنمو في منطقة سهل الجفارة ؟

المحاصيل	الاشجار
•	• ....
•	• ....
•	• ....
•	• ....

13. هل أنواع ونماذج المحاصيل التي تزرع بالمنطقة تغيرت خلال العشرين سنة الماضية ؟

نعم	لا	لا أعرف
☐	☐ إذهب الى السؤال 16	☐

إذا كانت الاجابة بنعم من فضلك اجب على السؤال أ ، ب

أ. ما ذا يكون الاختلاف ؟

....
....
......

ب. هل تعتقد أن ذلك التغير له علاقة بالتغير في المياه الجوفية ؟

نعم ☐   لا ☐   لا أعرف ☐

إذا الاجابة "لا" من فضلك اذكر السبب

- ....
- ....

14. هل التغير في التزود بالمياه الجوقية يؤثر علي نوعية المحاصيل والاشجار التي تزرع بهذه المنطقة؟

نعم ☐   لا ☐   لا أعرف ☐

من فضلك أذكر بالتفصيل

....
....
....

15. هل لديك أي ملاحظات أخرى لها علاقة بمستوى بالمياه الجوفية أو أي تعليق على فترة العشرين سنة الاخيرة ترغب في إضافته ؟

....
....
....
....
....
....
....

Appendix II-B3: a complete set of questionnaires responses.

How would you describe the quantity of groundwater in the 1980's?				
Shortage	Intermittent Supply	Sufficient	Not an issue	I don't know
4	7	61	8	5

How have groundwater quantity levels been in the last five years?				
Shortage	Intermittent Supply	Sufficient	Not an issue	I don't know
47	9	23	4	2

How does the ground water quantity today compare to that in the 1980's?			
Less water	Similar	More water	I don't know
73	10	0	2

What has been the groundwater quality over the last five years?				
Very Poor	Poor	Good	Very good	Excellent
8	38	30	8	1

What was the depth of the ground water level at the end of the 1980's?				
25-50 m	50-100 m	100-200m	Over 200m	I don't know
33	25	19	6	2

What was the depth of the ground water level in the year 2000?				
25-50 m	50-100 m	100-200m	Over 200m	I don't know
9	28	22	25	1

What is the depth of the ground water level now?				
25-50 m	50-100 m	100-200m	Over 200m	I don't know
8	19	12	44	2

Has there been any depletion of ground water levels in the last 20 years?			
Yes-major	None	Some	I don't know
48	15	16	6

What is the reason for the depletion of groundwater?			
Intensive use	Less precipitation	Both	I don't know
16	49	19	1

Has the pattern and types of crops/trees grown in this area changed during the past 20 years?			
Yes	No	Faintly	I don't know
42	20	15	8

Do you believe the change of the type crops/trees is related to the groundwater?			
Yes	No	I don't know	No answer
51	2	4	28

Appendix III

Header files of image 1988

```
PRODUCT =03063001409 WRS =189/037F  ACQUISITION DATE =19880825 SATELLITE
=L5 INSTRUMENT =TM10 PRODUCT TYPE =MAP ORIENTED    PRODUCT SIZE =FULL
SCENE
TYPE OF GEODETIC PROCESSING =SYSTEMATIC RESAMPLING =NN RAD GAINS/BIASES
=   +0.6024/-1.5000   +1.1749/-2.8000   +0.8059/-1.2000   +0.8145/-1.5000
+0.1081/-0.3700  +0.0552/+1.2378  +0.0570/-0.1500 TAPE SPANNING FLAG=1/1
START LINE #=     1 LINES PER VOL= 7060 ORIENTATION =   0.00 PROJECTION
=UTM  USGS PROJECTION # =      1 USGS MAP ZONE =     33 USGS PROJECTION
PARAMETERS     =0.637813700000000D+07                0.635675231400000D+07
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     EARTH ELLIPSOID =WGS 84                  SEMI-
MAJOR AXIS =6378137.000 SEMI-MINOR AXIS =6356752.314 PIXEL SIZE =30.00
PIXELS  PER  LINE=  7440  LINES  PER  IMAGE=  7060  UL  0112128.7546E
340608.3441N     163987.141    3779493.000 UR 0134633.3940E 340900.9255N
387157.156    3779493.000 LR 0134808.0344E 321425.8050N      387157.156
3567723.000 LL 0112609.6990E 321145.2536N      163987.141    3567723.000
BANDS PRESENT =1234567 BLOCKING FACTOR =    1 RECORD LENGTH = 7440 SUN
ELEVATION =54  SUN  AZIMUTH  =123  CENTER  0123532.9990E  331040.5029N
275527.125   3673593.000  3720   3530 OFFSET=   0 REVB
```

Heather file of image 1992

```
PRODUCT =03063001407 WRS =189/037F  ACQUISITION DATE =19920820 SATELLITE
=L5 INSTRUMENT =TM10 PRODUCT TYPE =MAP ORIENTED    PRODUCT SIZE =FULL
SCENE
TYPE OF GEODETIC PROCESSING =SYSTEMATIC RESAMPLING =NN RAD GAINS/BIASES
=   +0.6024/-1.5000   +1.1749/-2.8000   +0.8059/-1.2000   +0.8145/-1.5000
+0.1081/-0.3700  +0.0552/+1.2378  +0.0570/-0.1500 TAPE SPANNING FLAG=1/1
START LINE #=     1 LINES PER VOL= 7092 ORIENTATION =   0.00 PROJECTION
=UTM  USGS PROJECTION # =      1 USGS MAP ZONE =     33 USGS PROJECTION
PARAMETERS     =0.637813700000000D+07                0.635675231400000D+07
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     EARTH ELLIPSOID =WGS 84                  SEMI-
MAJOR AXIS =6378137.000 SEMI-MINOR AXIS =6356752.314 PIXEL SIZE =30.00
PIXELS  PER  LINE=  7456  LINES  PER  IMAGE=  7092  UL  0111905.1736E
340622.2006N     160321.000    3780052.500 UR 0134428.7267E 340917.8308N
383971.000    3780052.500 LR 0134606.4844E 321411.6189N      383971.000
3567322.500 LL 0112350.4611E 321128.3071N      160321.000    3567322.500
BANDS PRESENT =1234567 BLOCKING FACTOR =    1 RECORD LENGTH = 7456 SUN
ELEVATION =54  SUN  AZIMUTH  =118  CENTER  0123320.7476E  331040.5166N
272101.031   3673672.750  3728   3546 OFFSET=   0 REVB
```

Heather file of image 1996

```
PRODUCT =03063001412 WRS =189/037F  ACQUISITION DATE =19960815 SATELLITE
=L5 INSTRUMENT =TM10 PRODUCT TYPE =MAP ORIENTED    PRODUCT SIZE =FULL
SCENE
TYPE OF GEODETIC PROCESSING =SYSTEMATIC RESAMPLING =NN RAD GAINS/BIASES
=  +0.6024/-1.5000   +1.1749/-2.8000   +0.8059/-1.2000   +0.8145/-1.5000
+0.1081/-0.3700  +0.0552/+1.2378  +0.0570/-0.1500 TAPE SPANNING FLAG=1/1
START LINE #=      1 LINES PER VOL= 7124 ORIENTATION =   0.00 PROJECTION
=UTM  USGS PROJECTION # =        1 USGS MAP ZONE =      33 USGS PROJECTION
PARAMETERS      =0.637813700000000D+07                0.635675231400000D+07
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     0.000000000000000D+00     0.000000000000000D+00
0.000000000000000D+00     EARTH ELLIPSOID =WGS 84                   SEMI-
MAJOR AXIS =6378137.000 SEMI-MINOR AXIS =6356752.314 PIXEL SIZE =30.00
PIXELS   PER   LINE=   7456   LINES   PER   IMAGE=   7124   UL   0113012.8952E
340644.8049N      177464.594    3780147.250 UR 0135538.0825E 340927.2515N
401114.594     3780147.250 LR 0135701.7708E 321349.4403N      401114.594
3566457.250 LL 0113445.0540E 321118.4194N      177464.594     3566457.250
BANDS PRESENT =1234567 BLOCKING FACTOR =    1 RECORD LENGTH = 7456 SUN
ELEVATION =53   SUN   AZIMUTH   =114   CENTER   0124422.5228E   331040.5166N
289244.625    3673287.250   3728   3562 OFFSET=    0 REVB
```

Heather file of image 2000

```
PRODUCT =03063001404 WRS =189/037F  ACQUISITION DATE =20000826 SATELLITE
=L5 INSTRUMENT =TM10 PRODUCT TYPE =MAP ORIENTED   PRODUCT SIZE =FULL
SCENE
TYPE OF GEODETIC PROCESSING =SYSTEMATIC RESAMPLING =NN RAD GAINS/BIASES
=  +0.6024/-1.5000  +1.1749/-2.8000  +0.8059/-1.2000  +0.8145/-1.5000
+0.1081/-0.3700  +0.0552/+1.2378  +0.0570/-0.1500 TAPE SPANNING FLAG=1/1
START LINE #=     1 LINES PER VOL= 7148 ORIENTATION =  0.00 PROJECTION
=UTM  USGS PROJECTION # =       1 USGS MAP ZONE =     33 USGS PROJECTION
PARAMETERS =0.637813700000000D+07    0.635675231400000D+07
0.000000000000000D+00   0.000000000000000D+00   0.000000000000000D+00
0.000000000000000D+00   0.000000000000000D+00   0.000000000000000D+00
0.000000000000000D+00   0.000000000000000D+00   0.000000000000000D+00
0.000000000000000D+00   0.000000000000000D+00   0.000000000000000D+00
0.000000000000000D+00    EARTH ELLIPSOID =WGS 84              SEMI-
MAJOR AXIS =6378137.000 SEMI-MINOR AXIS =6356752.314 PIXEL SIZE =30.00
PIXELS PER LINE= 7468 LINES PER IMAGE= 7148 UL 0112120.6762E
340650.6826N    163826.656   3780805.750 UR 0134659.3115E 340943.7997N
387836.656   3780805.750 LR 0134834.5561E 321342.9446N    387836.656
3566395.750 LL 0112605.2599E 321102.0635N    163826.656   3566395.750
BANDS PRESENT =1234567 BLOCKING FACTOR =    1 RECORD LENGTH = 7468 SUN
ELEVATION =55 SUN AZIMUTH =125 CENTER 0123545.3346E 331040.5166N
275846.688   3673586.000  3734   3574 OFFSET=    0 REVB
```